THE IMPACT MECHANISM OF AI-DRIVEN SUPPLY CHAIN CREDITWORTHINESS ASSESSMENT ON COMMERCIAL BANKS' CREDIT POLICIES FOR SMEs

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ABSTRACT

This study explores how Artificial Intelligence (AI)-driven creditworthiness assessments within supply chains can reshape commercial banks' credit policies toward small and medium-sized enterprises (SMEs), aiming to address persistent SME financing challenges through technological innovation. Grounded in information asymmetry theory, relationship lending theory, group lending theory, and supply chain finance theory, the study tests five core hypotheses using structural equation modelling (SEM) based on survey data from 360 commercial banking professionals in China.

The results reveal that both SME credit status and core firm influence exert significant positive direct effects on bank credit policy (β = 0.285, β = 0.317, $p < 0.001$). Furthermore, AI-enhanced bank cognition plays a key partial mediating role in these

relationships, with significant indirect effects (β = 0.167, β = 0.193, $p < 0.001$). Notably, AI assessment accuracy demonstrates a significant positive moderating effect, with high-precision AI systems amplifying the influence on policy outcomes (β = 0.124, β = 0.138, $p < 0.001$). These findings suggest that AI fundamentally transforms SME credit assessment by improving risk evaluation precision, leveraging supply chain relational value, and enhancing banks' cognitive capabilities. The moderating role of AI system accuracy highlights the importance of technological maturity in optimizing AI's benefits.

This study provides robust empirical evidence that AI-enabled supply chain finance presents a viable pathway to easing global SME financing constraints while upholding sound risk management practices.

Keywords: Artificial Intelligence, supply chain finance, SME financing, credit policy, structural equation modelling, mediating effect, moderating effect

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Writing this indicates that I have completed my doctoral thesis, and I am about to become a real doctoral student. Looking back on this learning experience, I could not have done it without the help of my supervisors, my family, and my classmates.

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Wu Feng

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Chapter 1
Introduction

Rationale

The financing constraints faced by small and medium-sized enterprises (SMEs) are a significant obstacle to the development of the global economy, especially in the context of complex supply chain networks. In the current supply chain structure, core enterprises often adopt the 'payment after delivery' settlement method when purchasing raw materials due to their strong bargaining power. The suppliers upstream of the supply chain are primarily small and medium-sized enterprises (SMEs), which find it difficult to obtain credit support from traditional commercial banks due to their short establishment time, insufficient disclosure of information, and lack of sufficient collateral. This situation leads to the possibility that core enterprises may default on payments to upstream SMEs, and these SMEs cannot obtain loans from banks, thus triggering capital chain breaks and supply chain financial risks.

Traditional credit analysis methods have become insufficient when dealing with complex supply chain systems, highlighting the need to introduce innovative assessment methods. The rise of Artificial Intelligence (AI) technology provides a solution to this problem, which can significantly improve the accuracy and efficiency of credit risk assessment by analyzing massive amounts of structured and unstructured data. However, despite the potential of AI technology in risk assessment, there is a lack of in-depth empirical research on how AI-driven supply chain creditworthiness assessment affects commercial banks' credit policies towards SMEs and the underlying mechanisms of AI technology. Existing studies have not yet clarified how AI can effectively automate and upgrade traditional credit scoring systems, nor under what conditions these technologies yield optimal outcomes. This study addresses this gap.

Therefore, this study delves into the impact of AI-driven supply chain reputation assessment on commercial banks' SME credit policies. Specifically, this study identifies the mediating role of 'AI-enhanced bank cognition' and explores the moderating effect of 'AI assessment accuracy'. Based on information asymmetry theory, relationship lending theory, group lending theory and supply chain finance theory, this study reveals through empirical analyses how AI technology can reshape the traditional credit assessment process.

By introducing AI, commercial banks can assess the creditworthiness of SMEs more accurately, understand the influence of core enterprises more deeply, and thus optimise their credit policies. This influence mechanism is realised through multiple paths: AI enhances data processing capabilities, improves the accuracy of risk prediction, and enables real-time monitoring of supply chain dynamics. With the help of AI, commercial banks can not only better prevent credit risks, but also provide more accurate and efficient lending services to SMEs in the supply chain, thus resolving the financing dilemma of the supply chain and promoting its more efficient and stable operation. This study provides theoretical foundations and practical guidance for optimising commercial banks' credit policies, thereby advancing the high-quality development of supply chain finance through the empowerment of intelligent technologies.

Research Questions

1. To study the impact of SME creditworthiness and core business influence on commercial banks' credit policies under the AI assessment framework.

2. To study the mediating role of AI-enhanced bank cognition in the credit status of SMEs, the influence of core enterprises and the credit policies of commercial banks.

3. To study how the 'accuracy of AI assessment' moderates the impact of SMEs' creditworthiness and core firms' influence on commercial banks' credit policies.

Objectives

1. To examine the impact of AI-enabled SME creditworthiness and core business influence on commercial bank credit policy.

2. To analyze the mediating effect of 'AI-enhanced bank cognition' in the relationship between SMEs' credit status, core enterprises' influence and commercial banks' credit policies.

3. To explore the moderating role of 'AI assessment accuracy' in the above relationships, and clarify the boundary conditions for the impact of technological maturity on policy.

Research Hypothesis

H1: SME Credit Status has a positive influence on Commercial Bank Credit Policies.

H2: Core Enterprise Influence has a positive influence on Commercial Bank Credit Policies.

H3: SME Credit Status has a positive influence on AI-Enhanced Bank Cognition.

H4: Core Enterprise Influence has a positive influence on AI-Enhanced Bank Cognition.

H5a: AI Assessment Accuracy moderates the relationship between SME Credit Status and AI-Enhanced Bank Cognition.

H5b: AI Assessment Accuracy moderates the relationship between Core Enterprise Influence and AI-Enhanced Bank Cognition.

Scope of the Research

5.1 Scope of content

This paper investigates the impact of AI-driven supply chain reputation assessment on commercial banks' SME credit policies, incorporating the following variables:

(1) Independent variable

SME Credit Status (SCS): Measures business stability, repayment history, financial transparency, cash flow predictability, collateral adequacy and overall credit risk.

Core Enterprise Influence (CEI): Measures the reputation of the core enterprise, payment reliability, strength of supply chain position and certification effect.

(2) Dependent Variable

Commercial Bank Credit Policies (CBCP): Measures loan approval rates, credit line flexibility, interest rate concessions, collateral requirements, loan processing efficiency and overall policy support for SMEs.

(3) Mediator Variable

Commercial Bank AI-Enhanced Cognition (CBAEC): Enhanced cognitive capabilities developed by bank professionals through AI systems in assessing SME credit risk, including data processing, pattern perception, real-time assessment, insight generation and decision-making confidence.

(4) Moderating Variable

AI Assessment Accuracy (AAA): A measure of the reliability and effectiveness of an AI system independent of human intervention, including algorithmic prediction accuracy, data quality, model validation performance, system reliability and error rate minimization.

5.2 Population Scope

Purposive sampling was selected due to its suitability in targeting banking professionals with direct experience in credit assessment, ensuring that the responses captured expertise relevant to AI-driven supply chain finance. The research subjects were credit professionals at commercial banks in China. Questionnaires were distributed to 450 banking professionals at 1,833 commercial banks in China, and 360 valid questionnaires were returned, with a valid response rate of 80%.

5.3 Regional scope

This study conducted a survey sampling in five representative cities, Beijing, Shanghai, Guangzhou, Shenzhen, and Nanning, to ensure that the sample is diverse in terms of geography and level of economic development. Beijing and Shanghai represent national financial centres at the forefront of AI technology adoption; Guangzhou and Shenzhen represent developed market-based regional financial hubs; and Nanning represents regional differences in the Southwest.

5.4 Time scope

The survey period of this study is from January 2024 to December 2024.

Advantages

1. This study provides an empirical basis for commercial banks to apply AI technology to optimize credit decision-making, which helps to promote the in-depth application of AI in the financial sector and enhance the core competitiveness of banks.

2. By demonstrating that the AI-driven assessment model can effectively identify high-quality SMEs, this study provides a feasible technological path to alleviate the global SME financing gap problem and promotes the development of inclusive finance.

3. AI-enabled supply chain finance can effectively identify and manage risks and optimise capital flows, enhancing the resilience and competitiveness of the entire supply chain and promoting the healthy development of the real economy.

Definition of Terms

1. SME Credit Status

SME Credit Status is a comprehensive assessment of an SME's ability to repay its debts, which reflects the overall creditworthiness and financial soundness of the organisation. Under the AI assessment framework of this study, this concept goes beyond the traditional static financial statement analysis to cover more dynamic and multi-dimensional data. It encompasses not only the financial health of the enterprise, such as its asset-liability structure, cash flow predictability and profitability; it also encompasses its performance capability, i.e. the reliability of its contractual fulfilment and repayment history. It also pays high attention to a company's market reputation, including brand image, customer reviews and industry reputation, as well as its position in the supply chain, which determines the stability and importance of its business. Empowered by AI technology, these factors are integrated and analysed to form a comprehensive, real-time updated credit portrait that serves as a key basis for commercial banks' credit decisions.

2. Core Enterprise Influence

Core Enterprise Influence refers to the radiation effect that an enterprise in a dominant supply chain network has on the operation and credit eligibility of other SMEs in the chain (especially its upstream and downstream partners) through its market position, business relationship and credit strength. This influence is a key source of credit enhancement in supply chain finance. Its specific performance includes the core enterprise's own excellent risk management and control ability, which guarantees the stability of the whole supply chain; its strong relationship network and bargaining power, which brings stable orders and market opportunities for the associated SMEs; its good market reputation and brand influence, which constitutes an intangible credit endorsement to its partners; and its highly efficient information-sharing ability, which can reduce the information asymmetry between the bank and the SMEs. Information asymmetry between banks and SMEs. In the AI-driven assessment model, this influence is quantified into specific credit weights, enabling the 'soft power' of the core enterprise to be effectively recognised and transferred to SMEs.

3. Commercial Bank Credit Policies

Commercial bank credit policy refers to a set of principles, standards and specific operational processes on lending to SMEs developed and implemented by the bank with the support of the AI assessment system. It is the dependent variable that measures the ultimate effectiveness of AI-driven creditworthiness assessment. It is specified in several, some, many observable aspects, such as the leniency of the bank's credit approval criteria and the efficiency of the approval process; the provision of more flexible and adequate arrangements in terms of loan amount and maturity; the ability to offer more competitive and favourable terms in terms of interest rate and fee setting; and the flexibility in terms of guarantee and collateral requirements. A more proactive, accommodative and efficient credit policy means that banks, aided by AI technology, have a more precise grasp of risk and are thus more willing to support the development of SMEs.

4. Commercial Bank AI-Enhanced Cognition

AI-enhanced bank cognition refers to the deeper and sharper judgment beyond traditional analytical capabilities that commercial bank credit professionals gain through in-depth interaction and collaboration with AI credit assessment systems. It does not refer to the capabilities of the AI system itself, but instead emphasizes the cognitive sublimation that comes from human-machine collaboration. This enhanced cognition is reflected at multiple levels: firstly, the strengthening of data processing capability, which enables rapid digestion and understanding of massive and complex data; secondly, the improvement of risk pattern perception capability, which identifies subtle risk signals hidden behind data that are not easy to detect; then, the real-time dynamic assessment capability, which allows for rapid response based on real-time changes in the supply chain; and also includes the ability to integrate multi-source information to generate insights, and ultimately a significant increase in decision-making confidence aided by AI. In this study, it plays a key intermediary role as a cognitive bridge between objective credit data and subjective policy making.

5. AI Assessment Accuracy

AI assessment accuracy is an objective measure of the technical performance and reliability of the AI credit assessment system itself, independent of the subjective perception of the human user. This variable measures the 'hard power' of the AI tool, which directly determines its value in credit decision-making. Its assessment dimensions include: the algorithmic prediction accuracy of the AI model, i.e. the precision of its prediction of SME default risk; the quality and completeness of the input data on which the model relies; the validation performance and robustness of the model in the face of different market environments and data fluctuations; the reliability of the AI system and the consistency of the results over time; and the minimization of the error rate of the system in credit analysis, i.e. the reduction of misclassification of high-quality customers as inferior ones. reduces the probability of misclassifying high quality customers as poor quality customers (false negatives) and misclassifying poor quality customers as high quality customers (false positives). In this study, it serves as a key moderating variable that determines the strength of the AI-enabling effect.

Research Framework

This study systematically explores the mechanism of artificial intelligence (AI)-driven supply chain reputation assessment on commercial banks' credit policies for small and medium-sized enterprises (SMEs). In order to clearly reveal the complex relationship between the variables, this study constructs a comprehensive theoretical framework containing direct, mediating and moderating effects. The framework takes SME credit status and core enterprise influence as the core independent variables and commercial bank credit policy as the final dependent variable, and delves into the key role played by AI technology.

The core logic of the study lies in the fact that the intervention of AI not only directly influences the final decision of banks, but also reshapes the entire assessment system through a key cognitive mediation process. Specifically, this study proposes that 'AI-enhanced bank cognition' plays an important mediating role between the independent variable and the dependent variable. This means that the good credit standing of SMEs and the strong influence of core firms will first be translated into a deeper and more accurate risk perception and opportunity judgment by bank credit officers through the AI system. Then this AI-enhanced cognition will further drive banks to formulate more favorable credit policies. This intermediary path reveals the transformation of AI technology from a 'tool' to a 'cognitive amplifier'.

At the same time, this study recognizes that the actual effectiveness of AI technology is not static and that its maturity and accuracy are critical. Therefore, this study introduces 'AI assessment accuracy' as a key moderating variable. It is hypothesized that a highly accurate AI assessment system can significantly amplify (i.e. enhance) the positive impact of SMEs' creditworthiness and core business influence on banks' perceptions and ultimately their credit policies. Conversely, a low-accuracy system may weaken or even distort this impact. The introduction of this moderating mechanism enables this research framework to more realistically reflect the determining role of technological quality in applying financial innovation.

In summary, the theoretical model of this study contains five core hypothesis paths: the first and second paths test the direct effect of SMEs' credit status and core firms' influence on commercial banks' credit policy; the third and fourth paths test the indirect effect of these two factors on credit policy through the mediator variable of 'AI-enhanced bank perception'; and the fifth path tests the indirect impact of these two factors on credit policy through the mediator variable of 'AI-enhanced bank perception'. The third and fourth paths examine the indirect effects of these two factors on credit policy through the mediating variable of 'AI-enhanced bank cognition'. In contrast, the fifth path explores how 'AI assessment accuracy' moderates the strength of the overall influence process. Together, these relationships form a complete, multilevel model of the impact mechanism. The specific relationships and hypothesised paths are shown in Figure 1.1.

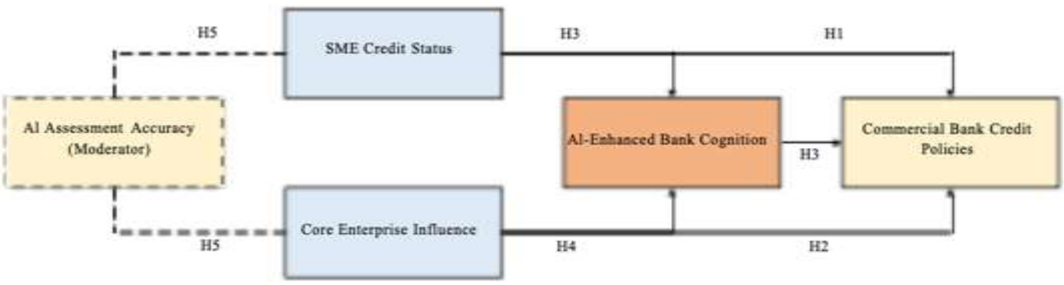

Figure 1.1 Research Framework

Chapter2
Literature Review

This chapter provides theoretical and empirical support for the research model and variables to justify the research content. On the theoretical level, this paper is based on the information asymmetry theory, relationship lending theory, group lending theory and supply chain finance theory, in which the information asymmetry theory mainly reveals that commercial banks are not able to fully understand the information of SMEs because of the inability of commercial banks to make credit decisions. Relationship lending theory mainly reveals the relationship between mature commercial banks and SMEs, which is conducive to commercial banks obtaining more information about SMEs and thus making better credit decisions. Group lending theory mainly reveals the mutual guarantee relationship between core enterprises and SMEs in the supply chain, which creates favorable conditions for commercial banks to make credit decisions. The theory of supply chain finance mainly reveals that core enterprises in the supply chain guarantee for medium-sized and small enterprises, to provide theoretical support for commercial banks' supply chain finance business. This paper explores how AI technology can revolutionize these classical theories.

At the empirical level, this chapter will comb through the relevant literature to support the reasonableness of the hypothesized relationships between the variables (independent, dependent, mediating and moderating variables). Therefore, this chapter provides relevant support for previous scholars' research results, mainly in the following aspects.

1. General Theory of Influencing Factors of SME Credit in Commercial Banks
2. The relationship between SME credit and commercial bank credit policy (H1)
3. Relationship between core business impact and commercial bank credit policy (H2)

4. The mediating role of AI-enhanced bank cognition (H3, H4)
5. Moderating role of AI in assessing accuracy (H5)
6. Relationship between firm creditworthiness and observables
7. Relationship between core business impacts and observatories
8. Relationship between commercial bank perceptions and observables
9. Relationship between commercial bank credit policy observatories
10. Other relevant studies

General Theory of Supply Chain Finance Credit Impact on Medium and Small Businesses in Commercial Banks

1. Information asymmetry theory

The information asymmetry theory was first proposed by George Akerlof (1970), who led to market failure by analyzing the information asymmetry in the used car market. The information asymmetry theory refers to a situation where two or more parties to a transaction or decision-making process do not have equal information. This information asymmetry may lead to problems such as market failure, adverse selection and moral hazard. In financial lending, information asymmetry manifests itself in the passive position of commercial banks in the process of loan disbursement because they do not have full knowledge of the borrower's repayment ability and the purpose of the loan.

In terms of borrower-initiated disclosure, Moro, A., Fink, M., & Kautonen, T. (2019) suggested that borrower-initiated disclosure of financial and non-financial information can help banks to more accurately assess credit risk, which in turn is more conducive to the chances of obtaining bank loans. Chen, Y., Chen, H., Huang, S., & Wang, Y. (2020) argued that voluntary disclosure of information by borrowing firms during the loan application process can significantly reduce information asymmetry and thus improve the loan approval rate. Bharath, S. T., Sunder, J., & Sunder, S. V. (2020) argued that the quality of accounting information and voluntary disclosure of information play an important role in improving the loan terms of borrowing firms. Borrowing firms can significantly reduce information asymmetry through high-quality accounting information and voluntary disclosure behavior, which in turn facilitates better loan terms. Cumming, D. J., Leboeuf, G., & Schwienbacher, A. (2021) studied the effect of different funding models on information asymmetry. They argue that the 'all-or-nothing' model can effectively incentivize borrowers to voluntarily disclose information and reduce information asymmetry more than the 'keep-it-all' model, thus making it easier for them to obtain loans. Li, X., & Wang, Q. (2021) found that Chinese firms that voluntarily disclose more information receive loans with lower interest rates and longer loan terms. Gao, P., & Meng, Q. (2021) found that medium-sized and small firms in emerging markets that voluntarily disclose information about their financial status and operations favor obtaining better lending terms. Martínez-Sola, C., García-Teruel, P. J., & Sá nchez-Ballesta, J., & Sá nchez-Ballesta, J., & Sá nchez-Ballesta, J. (2022). nchez-Ballesta, J. P. (2022) found that there is a positive correlation between board independence and the effectiveness of borrowing firms' voluntary disclosure of information, the stronger the board independence, the more effective the borrowing firms' voluntary disclosure of information, which is conducive to the borrowing firms to reduce the cost of loans. Wang, Y., & Zhang, Y. (2022) showed that the more competitive the market environment is, the more willing firms are to voluntarily disclose information, which increases the financing rate by reducing information asymmetry. Kim, J. B., & Zhang, L. (2023) argued that voluntary disclosure of information by firms contributes to improving the friendliness of loan contract conditions. Xu, N., & Wang, R. (2023) argued that voluntary disclosure of information by firms is conducive to increasing the possibility of obtaining loans from banks. Huang, Y., & Zhang, Y. (2022) argued that voluntary disclosure by firms is conducive to increasing the possibility of obtaining loans from banks. Huang, Z., & Li, J. (2024) showed that with higher financial transparency, firms are more likely to obtain longer-term debt financing through voluntary disclosure.

In terms of commercial banks proactively mitigating information asymmetry, Petersen, M. A., & Rajan, R. G. (2019) argued that commercial banks can build a long-term good relationship between commercial banks and borrowing firms, which helps commercial banks to reduce information asymmetry and be more prepared to assess credit risk. Moro, A., & Fink, M. (2019) found that advanced information systems facilitate commercial banks' judgment of medium and small enterprises and mitigate the information asymmetry challenge, thus improving the efficiency of credit extension. Beck, T., Pamuk, H., Ramrattan, R., & Uras, B. (2020) Firms using electronic payment instruments mitigate the information asymmetry due to greater financial transparency. Thus such firms are more likely to obtain loans from commercial banks. Berger, A. N., & Frame, W. S. (2020) argue that big data and artificial intelligence can help commercial banks assess SMEs' credit risk more efficiently and reduce losses from information asymmetry. Berger, A. N., & Frame, W. S. (2021) argue that the use of big data and artificial intelligence can help commercial banks to reduce information asymmetry in the lending process and improve the accuracy and efficiency of credit assessment. Chodorow-Reich, G., & Falato, A. (2021) concluded that commercial banks can improve the security of their loans and reduce the losses caused by information asymmetry by adding more conditions in the loan covenants. Carbó- Valverde, S., Cuadros-Solas, P., & Rodríguez-Fernández, F. (2022) study concluded that in the digital era commercial banks and borrowing firms build good relationships over time can help to mitigate information asymmetry and improve lending efficiency. Berger, A. N., & Roman, R. A. (2022) verified through empirical analysis that big data and artificial intelligence play an essential role for commercial banks to alleviate information asymmetry and reduce credit risk of commercial bank credit. Hau, H., & Thum, M. (2023) argued that digital platforms improve information transparency, help commercial banks to make accurate judgments, reduce information asymmetry, and promote commercial banks to provide loans to medium and small enterprises. loans. Degryse, H., Ongena, S., & Zhang, R. (2023) suggest that bank mergers can break down information barriers, reduce information asymmetry, and improve credit efficiency. Berger, A. N., & Frame, W. S. (2024) argue that AI can help to reduce information asymmetry, but the development of AI also raises new issues of regulation and competition.

In terms of national policies to mitigate information asymmetry, Allen, F., Gu, X., & Kowalewski, O. (2019) examined national policies in Poland. He suggested that the use of national policies to enhance the transparency of the financial market and to establish an information-sharing mechanism can significantly mitigate information asymmetry and promote commercial bank lending to small and medium-sized enterprises (SMEs). Beck, T. Ioannidou, V., & Schäfer, L. (2019) argued that the state can help alleviate information asymmetry in an essential way by requiring commercial banks to increase their capital adequacy ratios and improve information disclosure. Li, X., & Zhang, J. (2020) examined the Chinese government's policy of guarantees for medium- and small-sized enterprises, and argued that government guarantees are conducive to reducing bank credit risk, mitigates the effects of information asymmetry, and facilitates credit access for medium and small enterprises. Carbó-Valverde, S., & Rodríguez-Fernández, F. (2020) examined the impact of Spanish government policies on medium and small enterprises, and concluded that the government's credit guarantees, and interest rate subsidies help to mitigate information asymmetry and play an essential role in the credit access of medium and Berger, A. N., & Roman, R. A. (2021) argue that strengthened government regulatory and disclosure policies can help to alleviate information asymmetry in commercial banks' access to credit for medium-sized and small firms. Gambacorta, L., & Shin, H. S. (2021) argue that policies that require commercial banks to raise their capital gains can help to increase the transparency and transparency of commercial banks. Gambacorta, L., & Shin, H. S. (2021) argued that requiring commercial banks to increase their capital gains is conducive to improving the transparency and risk resistance of commercial banks, which plays an essential role in alleviating the information asymmetry and enhancing the efficiency of credit. Wang, Y., & Zhang, Y. (2022) argued that the Chinese government's policy of subsidizing the information disclosure of small and medium-sized enterprises (SMEs) when applying for credit from commercial banks helps to alleviate the information asymmetry and is essential.in assisting the SMEs to obtain loans. Obtaining loans is of significant help.

The rise of Artificial Intelligence (AI) technology has provided a revolutionary solution to overcome the information asymmetry that has long plagued the financial industry. The core strength of AI lies in its powerful data processing and pattern recognition capabilities, which enable it to extract insights from large volumes of multi-dimensional, unstructured data beyond the reach of traditional credit review methods. Today's AI systems are no longer limited to analysing static financial statements. Still capable of integrating and processing 'alternative data' including corporate transaction flows, logistics information, utility bill payments, and even social media reputations. This AI-driven big data analysis can construct a more comprehensive, dynamic and accurate corporate credit portrait, greatly bridging the information gap between banks and SMEs. As shown in the study by Zhu et al. (2019), the accuracy of using an enhanced hybrid integrated machine learning approach to predict the credit risk of SMEs in supply chain finance far exceeds that of the traditional model, which directly proves the great potential of AI in reducing the information disadvantage of banks.

The role of AI in mitigating information asymmetry in practice has been proven at several levels. First, AI technology can effectively utilise data endogenous to the supply chain. In complex supply chain networks, the risks of SMEs are often closely related to the health of the entire chain. AI can significantly improve the transparency of operations such as inventory pledge financing by analysing real-time data generated by Internet of Things (IoT) devices and tamper-proof transactions recorded on blockchain, effectively reducing the risks arising from information opacity. Second, government-led digital reform also creates favorable conditions for AI applications. Jiang and other scholars' (2025) study of China's digital tax reform found that the system improves the transparency and reliability of corporate financial and tax information through technological means, which enables AI models to conduct more accurate risk assessments based on this high-quality data, thereby reducing information asymmetry-induced stock price variations and other market risks. Finally, the dynamic analysis capability of AI is particularly critical when dealing with external shocks. Drydakis (2022) shows that during the COVID-19 pandemic, those SMEs that applied AI for customer targeting, cash flow management, and human resource deployment exhibited stronger risk resilience, which fully demonstrates the unique value of AI in coping with sudden market fluctuations and bridging the information vacuum. The unique value of AI in addressing sudden market fluctuations and bridging information vacuums.

Many scholars have examined the impact of information asymmetry on commercial banks' credit policies, yet few have explored leveraging artificial intelligence to bridge the gap of 'information unavailability' faced by these institutions. This paper employs a data-driven dynamic governance mechanism to transfer the 'information advantage' from enterprises to banks and regulators, thereby reshaping the credit ecosystem for small and medium-sized enterprises.

2. Relationship lending theory

The theory of relationship lending was proposed by Allen N. Berger, Gregory F. Udell (1995). Relationship lending refers to the process of long-term co-operation between commercial banks and lending enterprises, obtaining soft information such as management and corporate culture of the lending enterprises, to reduce the asymmetry of information, reduce the risk of credit, and improve the efficiency of credit. They proposed for the first time the role of relationship lending in commercial banks to medium-sized and small enterprises. Relationship lending mainly includes the aspects of soft information accumulation, credit risk reduction, credit decision optimization and customer loyalty enhancement.

Carbó-Valverde, S., Rodríguez-Fernández, F., & Udell, G. F. (2019) found that the establishment of long-term relationships between banks and firms contributes to the supply of credit. Ghosh, S., & Sen, S. (2020) found that the establishment of an informal social relationship between a commercial bank and a firm has a significant impact on the commercial banks to obtain information about the firms. Petersen, M. A., & Rajan, R. G. (2021) argued that the establishment of long-term relationships between commercial banks and borrowing firms could help the banks to effectively assess the risk of the borrowers. Elsas, R., & Krahnen, J. P. (2021), by examining the German credit data, suggested that relationship lending can help the commercial banks to obtain more comprehensive information, and the commercial banks to obtain more comprehensive information. Commercial banks to obtain more comprehensive information and reduce information asymmetry.

Advances in Artificial Intelligence (AI), particularly Natural Language Processing (NLP) and Machine Learning, are profoundly reshaping the paradigm of relationship lending practices, with AI innovations making it possible, for the first time, to capture, quantitatively analyze, and objectively assess 'soft information' at scale. Advanced AI systems can automatically capture and analyze vast amounts of unstructured text data from news reports, industry forums, customer reviews, social media interactions, and even business-to-business email exchanges, extracting key soft information about corporate reputation, management dynamics, market sentiment, and more. As explored in Francesco and La's (2023) study, digitalization is changing the value of the bank-firm relationship, with AI technologies transforming the traditional "relationship" signals, which relied on interpersonal interactions, into quantifiable, traceable, and comparable digital portraits, allowing the benefits of relationship lending to be applied on a broader scale [9]. The benefits of relationship lending can be applied on a wider scale.

AI not only evaluates static soft information, but also dynamically captures and measures a firm's "resilience", a key attribute that is extremely difficult to quantify in traditional relationship lending. In times of economic crisis or industry turmoil, the ability of firms to survive and thrive is of paramount concern to banks, and Madhavika et al.'s (2024) study of the supply chains of Sri Lankan construction SMEs reveals the importance of resilience. The AI model can be used to analyse the frequency of communication within the supply chain, the stability of orders, the ratings of suppliers, and public opinion reactions to external shocks, to construct a quantitative 'resilience index'. 'resilience index'. This ability enables banks to go beyond simple historical data to make forward-looking judgments on the future risk resistance of enterprises, thus upgrading relationship lending from an artistic empirical judgement to a data-driven scientific decision. This not only improves the efficiency and accuracy of credit decisions, but also allows more SMEs with 'invisible' advantages to be identified by the financial system.

Many scholars have studied the impact of information asymmetry on commercial bank credit policy, but few have focused on the use of artificial intelligence to bridge the gap of 'information unavailability' in commercial banks. This paper reshapes the credit ecosystem of SMEs through a data-driven dynamic governance mechanism that transfers the 'information superiority party' from enterprises to banks and regulations.

3. Group lending theory

The theory of group lending was first proposed by the Bangladeshi economist Muhammad Yunus. Group lending refers to financial institutions gathering the borrowers together, giving them loans, this group of borrowers share the responsibility of repayment. Each borrower is not only responsible for their borrowing, but also needs to bear the other borrowers of the loan's rich joint and several liability. By monitoring each other within the group, each member is incentivized to repay the loan on time.

Ahlin, C., & Townsend, R. M. (2019) argued that group lending could effectively reduce borrower default rates. Giné, X., & Karlan, D. (2019) argued that group lending can be effective in reducing default rates in the short term by examining microfinance data in the Philippines, but that the long term effect depends on the dynamics of the borrowing group and management Attanasio, O., Augsburg, B., De Haas, R., Fitzsimons, E., & Harmgart, H. (2020) By examining joint liability lending in Mongolia, it is concluded that group lending significantly improves the profitability of the borrower while reducing the risk of default. Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2020) concluded that group lending significantly improves the loan success rate of borrowing firms through a randomised assessment methodology. Brau, J. C., & Woller, G. M. (2021) found that group lending has a different effect on mitigating information asymmetry in various economic environments and cultural contexts. Hermes, N., & Lensink, R. (2021) find that group lending has a significant role in reducing information asymmetry, and Karlan, D., &

Zinman, J. (2022) study group lending in Mexico and find that group lending can be effective in reducing the risk of default of the borrowing firms through the joint liability pressure. Bhatt, N., & Tang, S. (2023) analyzed data from a loan program in India and found that group size, type of membership, and linkages between members affect group loan repayment rates. Cull, R., Demirgüç-Kunt, A., & Morduch, J. (2023) found that group lending diversifies the credit risk of commercial banks Jain, S., & Mansuri, G. (2024) studied group lending in Pakistan and concluded that mutual monitoring among members of group lending could effectively reduce credit risk. Agier, I., & Szafarz, A. (2024) studied data on group lending in Brazil and found that member bonding and social capital can significantly improve repayment rates. Capital can significantly increase repayment rates.

Artificial intelligence technology has injected new vigor into the application of group lending theory in modern supply chain finance, and its core contribution lies in its robust network analysis and dynamic risk assessment capabilities. Traditional group lending or supply chain finance assessment is often stuck on a single linear 'axis-spoke' relationship of core enterprise-SMEs. AI technology, especially graph computing and network analysis algorithms, can treat the entire supply chain as a complex, dynamic 'social network', and can accurately identify key nodes in the network (not only core enterprises, but also some key secondary suppliers), the conduction paths of information and capital flows, and the possible ways of risk diffusion in the network. The way risks are likely to spread in the network. This enables banks to get a macro view of the health and systemic risk of the entire supply chain community, rather than just assessing individual members.

Enabled by AI, banks can build adaptive group lending models to cope with the complexity of modern supply chains and the volatility of markets. Kaur et al. (2023) hailed supply chain finance as an 'antidote' to the plight of small and medium-sized enterprises (SMEs) amid the economic crisis, and AI is the catalyst that multiplies the effectiveness of this antidote. 'AI system can dynamically adjust the risk weight of each member of the supply chain 'group' based on real-time transaction data, logistics information and market opinions. For example, when a key supplier is experiencing operational difficulties, AI can quickly predict the potential knock-on effects on downstream SMEs and provide early warning to the bank. This assessment model, which is based on the dynamic health of the entire 'group', is far more accurate and forward-looking than traditional static assessments. It not only improves the risk management level of banks, but also provides more solid theoretical and technical support to alleviate the financing constraints faced by SMEs in general, making the wisdom of group lending sublimated in the context of the new era.

Current research on syndicated lending continues to confine joint liability to interpersonal solidarity and core-enterprise hub-and-spoke guarantees, overlooking the multi-tiered nodes and dynamic coupling risks within supply chain networks. This oversight renders existing theories inadequate for explaining systemic default contagion within modern complex chains. This study reconfigures traditional syndication by upgrading peer oversight from static interpersonal constraints to algorithm-driven network-level monitoring. This approach fills a critical gap in syndicated lending theory by addressing its dynamic and systemic dimensions.

4. Supply Finance Theory

Supply chain finance is defined as the process in which financial institutions provide financial services to core and upstream and downstream enterprises in the supply chain by integrating the information, logistics and capital flows of the supply chain for the purpose of reducing the cost of supply chain financing and improving the efficiency of financing.

Wuttke, D. A., Blome, C., Heese, H. S., & Protopappa-Sieke, M. (2019) argued that supply chain finance has environmental impacts on borrowing firms' finances and operations. Zhan, W., & Yin, S. (2020) examined supply chain finance in China, and concluded that supply chain finance could significantly improve the Chen, L., & Hu, J. (2021) argued that the credit risk transfer mechanism of supply chain finance has a direct impact on the performance of borrowing firms, and Xu, X., & Zhang, X. (2021) found that supply chain finance can effectively alleviate the financial pressure of firms in the supply chain. Wang, J., Chen, W., & Huang, X. (2022) found that supply chain finance can effectively alleviate the financial pressure of firms in the supply chain. X. (2022) argued that blockchain technology can play an essential role in reducing transaction costs and improving transaction transparency for supply chain enterprises. Tang, C. S., & Zimmerman, J. D. (2022) found that optimizing credit requirements of commercial banks can significantly improve the efficiency of supply chain capital flows and operations. Tseng, M. L., Wu, K., & Chiu, A. (2021) found that supply chain finance can effectively alleviate the financial pressure of supply chain enterprises. Wang, J., Chen, W., & Huang, A. (2021) found that supply chain finance can effectively alleviate the financial pressure of supply chain enterprises. Tseng, M. L., Wu, K. J., & Chiu, A. S. (2023) argued that the development of green finance plays a vital role in solving the obstacles of supply chain finance and the sustainable development of supply chain finance. Li, Y., & Chen, Y. (2023) argued that the digital transformation has an essential impact on the improving of supply chain finance efficiency and transparency. Zhao, X., & Wang, Q. (2024) argued that there are certain risks in supply chain finance. L. (2024) argued that there are certain risks in supply chain finance, and proposed a network-based risk assessment and control method. L. (2024) argued that it is beneficial to promote the development of supply chain finance through further innovation.

The integration of artificial intelligence (AI) technology is driving the theory of supply chain finance from a relatively static and passive model to a dynamic, active and intelligent new stage of evolution. The core role of AI is to play the role of the entire supply chain's 'intelligent brain', which is capable of real-time capture, processing and analysis of massive data from the 'three streams'. It can capture, process and analyse huge data from the 'three streams' in real time. Through machine learning models, AI can accurately predict the future cash flow of the supply chain, dynamically assess the performance risk of the counterparty, and adjust the amount, interest rate, and term of the financing scheme in real time according to the rapidly changing market conditions. Wang and other scholars (2023) found that efficient supply chain finance can significantly improve the innovation efficiency of manufacturing SMEs. Driven supply chain finance maximizes the utility of financial support by providing more timely and accurate financial support, freeing enterprises from cumbersome financing matters to focus more on their core business and technological innovation.

In addition, the synergy of AI with other cutting-edge technologies is building a more robust and trustworthy supply chain finance ecosystem. A study by scholars such as Bae et al. (2025) explores the role of blockchain technology in the structure and governance of supply chain finance. Blockchain, with its decentralised, untamperable and traceable nature, provides a single, trusted data source for all transactions and information flows in the supply chain. AI, on the other hand, builds on this foundation to leverage its powerful analytical and decision-making capabilities. One can imagine a scenario: every transaction and every shipment of goods are recorded on the blockchain in real time, while the AI model continuously analyses these trusted data, and once anomalies (such as delivery delays and quality issues) are detected, it can immediately trigger a risk warning and automatically adjust the credit limit of the relevant enterprise. This powerful combination of AI and blockchain not only dramatically improves the transparency and financing efficiency of the supply chain, but also opens up a broad prospect for the future development of supply chain finance theory, enabling it to serve the real economy in a safer and more innovative way.

While prior studies confirm that group lending reduces default risk through mutual monitoring, little attention has been paid to how AI can enhance these mechanisms by modeling real-time network interactions. This thesis extends the theory by integrating AI-driven network analysis into group lending dynamics.

The relationship between SME credit and commercial bank credit policy (H1)

The creditworthiness of small and medium-sized enterprises (SMEs) has long been a vital assessment indicator in the credit policies of commercial banks. The traditional credit system usually relies on static data such as financial statements, collateral assets and historical repayment records when assessing enterprise credit risk. This approach often suffers from a lack of accuracy and comprehensiveness when dealing with small and medium-sized enterprises (SMEs) with asymmetric information, small business size and incomplete data. However, the rapid development of Artificial Intelligence (AI) technology is reshaping this assessment process, making the link between creditworthiness and credit policy more dynamic and refined. AI models, especially machine learning and deep learning algorithms, can synthesize both structured and unstructured data and conduct multi-dimensional analysis of enterprises, thus significantly improving risk identification capabilities and credit decision-making efficiency.

Taking Gao et al. (2021) as an example, the researchers proposed a 'soft-voting integrated model', which integrates mainstream algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, XGBoost, and LightGBM for assessing the credit risk of small and medium-sized enterprises (SMEs) in China. The model showed higher predictive accuracy than a single machine learning model in real bank data tests, significantly enhancing the science and differentiation of credit policy. In addition, Jayanandini and Gautami (2024) highlight that the introduction of a fusion model of behavioral economics and AI technology in the risk management process not only improves the predictive ability of the model, but also reveals the deeper relationship between borrowers' behavioral patterns and repayment willingness, which leads to a more forward-looking and inclusive credit policy. The role of AI for credit policy is not limited to the improvement of the model. Brown (2024) finds that AI-driven models outperform traditional models in identifying high-risk borrowers, especially after the application of interpretable AI (XAI) technology, which improves the transparency and credibility of credit models and enhances compliance and customer trust in bank decision-making. And Swankie and Broby (2019) further pointed out that AI not only helps in credit risk assessment, but also assists in managing liquidity risk and reputational risk, providing banks with a more comprehensive risk management system and helping to improve overall financial stability [20]. At the macro level, AI assessment systems are helping banks reconfigure the logic of credit resource allocation. Huang et al. (2020) conducted a study using 1.8 million SME loan data from a Chinese online bank as a sample. They found that FinTech credit models based on big data and AI technology still showed stronger risk identification capabilities under the impact of the epidemic. These models can not only identify potential risks missed by traditional credit scoring, but also serve SMEs that lack collateral and have weak credit histories but strong actual operating capabilities, enabling more accurate financial inclusion support. In summary, the intervention of artificial intelligence significantly strengthens the linkage mechanism between SMEs' credit status and commercial banks' credit policies. Ai not only improves the accuracy and efficiency of credit risk assessment, but also provides commercial banks with a more resilient and forward-looking decision-support tool in an uncertain economic environment.

Relationship between core business impact and commercial bank credit policies (H2)

In the modern supply chain finance system, the credit capacity and market discourse of core enterprises are considered to be an essential bridge connecting credit transmission between banks and SMEs. The traditional credit assessment approach focuses on the financial status of SMEs themselves and ignores their nested relationships in upstream and downstream networks. The development of AI technology, especially the breakthroughs in complex network analysis and big data integration, has enabled banks to more accurately assess the contribution of the core enterprises to the stability of their supply chains and the indirect credit influence transmitted by them.

As pointed out by Wan & Cui (2024), fintech (including AI, big data, and blockchain) greatly enhances banks' ability to identify credit risks of supply chain participants. Through an evolutionary game model, they find that an AI-driven risk assessment mechanism significantly improves the trust collaboration between banks and core firms and SMEs, thereby effectively reducing financing risks in agricultural supply chains. This mechanism is also applicable to the manufacturing and retail sectors, and its core lies in the visualization of data sharing and credit mechanisms through AI. Meanwhile, Chen et al. (2022) found that the credit indicators of core enterprises play a key role in the credit risk assessment of online supply chain finance, the degree and path of credit reliance on core enterprises varies across different industries by analysing the supply chain finance data of 368 small and medium-sized enterprises (SMEs) in four major industries in China. In addition, Mou et al. (2018) constructed a core enterprise credit risk assessment system based on fuzzy hierarchical analysis (FAHP), which for the first time integrates the core enterprise's asset status, industry influence, credit record, and its dynamic interaction data with upstream and downstream enterprises into a single information database, which is used to support the bank's comprehensive assessment of the 'chain credit transmission' in formulating its lending strategy. "The study further suggests that only a core group of firms with a strong credit history can be used to assess the creditworthiness of a chain. The study further suggests that only a data interaction platform centred on core enterprises can truly realise the dynamic perception and sharing of risks of enterprises at each node in the supply chain, and thus improve the confidence and precision of banks in the financing behaviour of the entire chain. Xie (2022), on the other hand, from the blockchain perspective, suggests that open collaboration of enterprise credit data is the key for banks to identify indirect credit dependencies in supply chain finance. Of the key. Through evolutionary path modelling, it is found that introducing a third-party information regulator combined with AI can strengthen the 'endorsement' function of the core enterprise credit, effectively avoiding the risk of fraudulent lending by upstream and downstream enterprises in fictitious transactions. This mechanism constitutes a 'collaborative credit guarantee system based on data consensus', which has a far-reaching impact on commercial banks' optimization of supply chain credit policy. Therefore, AI technology not only amplifies the credit value of core enterprises in the credit system, but also enables banks to provide financial support to SMEs in the chain with lower risk and higher efficiency through real-time mining, identification and modeling of credit transmission paths in the complex network of the supply chain. Core enterprises are not only passive sources of information, but also become credit anchors in the data-driven financial structure, which is an essential basis for commercial banks to formulate credit policies.

The mediating role of AI-enhanced bank cognition (H3, H4)

Bank cognitive capacity has long been recognized as one of the core drivers of credit decision-making, the essence of which lies in the bank's combined judgment of the borrower's repayment capacity and risk profile. Traditional cognitive processes are significantly influenced by experience, subjective preferences and information asymmetry, often leading to lagging, inconsistent or overly conservative decisions. The rise of AI technology is pushing this cognitive paradigm toward 'Augmented Cognition', i.e., through algorithmic models and data support systems, empowering rather than replacing the judgment of bankers. This 'human-computer collaborative' approach to cognition has become an essential intermediary mechanism between corporate creditworthiness and credit policy.

Abdul-Azeez et al.'s (2024) study points out that AI and data analytics technologies enable banks to mine multiple sources of heterogeneous data from transaction histories, social networks, and market sentiments in real time to construct a more dynamic and comprehensive portrait of SMEs. This AI-enabled cognition not only enhances the accuracy of credit assessment, but also allows banks to develop personalized credit products and risk control mechanisms, thereby improving financial inclusion for SMEs. The AI system plays a decisive role in assisting creditors in forming risk perceptions and selecting credit strategies [26]. Edunjobi and Odejide (2024), on the other hand, from the perspective of theoretical modeling, have explained how AI systems can enhance the accuracy and responsiveness of banks in credit risk assessment through machine learning and natural language processing algorithms. Compared to traditional models, AI frameworks have demonstrated greater adaptability and predictive capabilities in the face of massive, unstructured data, thus becoming an essential building block of banks' cognitive systems. This capability allows banks to not only distinguish risk levels more accurately, but also identify potential default risks earlier in the system's early warning mechanism, to optimise credit allocation strategies. Narang et al. (2024) emphasise that in AI-assisted banking operations, the cognitive system is being redefined as a closed-loop 'real-time perception-modelling-decision' process. Decision-making" closed-loop structure.

In this structure, AI is not only a tool for information integration, but also guides bankers to identify new types of risk and behavioural characteristics through algorithmic logic. For example, through emotion recognition and semantic analysis technology, banks can anticipate a customer's willingness to pay or the likelihood of fraud at the enquiry stage, enabling smarter initial credit screening. Such cognitive enhancement mechanisms can also significantly improve the stability of banks' decision-making in the face of uncertainty. Jaiswal and Akhilesh's (2019) study demonstrates the widespread penetration of 'cognitive AI' in banks' internal decision-making, especially in credit management for small and medium-sized enterprises (SMEs), where the interpretive analytics and knowledge-graphic capabilities provided by AI can be used. Interpretive analytics and knowledge graph capabilities enable credit officers to better understand the credit composition and change path of a business. This transparent and interactive cognitive process enhances banks' ability to grasp complex lending behaviors, and contributes to the transformation of credit policy from 'experience-oriented' to 'data-driven'. In sum, AI not only improves bank efficiency at the data processing level, but also builds a highly responsive and interpretive decision-making environment in the cognitive mechanism, making it an essential mediator between SMEs' creditworthiness and the influence of core firms on credit policy.

The moderating role of AI in assessing accuracy (H5)

The application of Artificial Intelligence (AI) systems in credit assessment not only changes the way of data processing, but also crucially affects the credibility and operability of assessment results. Especially in SME financing scenarios, the prediction accuracy of AI models directly determines whether they can effectively play the role of promoting financial inclusion and optimizing resource allocation. The higher the accuracy of AI assessment, the stronger its ability to identify the real credit status of enterprises and structural credit signals in the chain, which is more likely to be transformed into the credit confidence of banks and ultimately affect the degree of policy leniency. In other words, the accuracy of AI plays a significant moderating role between SMEs' credit status, core firms' influence and banks' credit policies.

Shittu (2022) systematically assesses how AI-driven credit risk models can enhance model accuracy through big data and machine learning. He points out that AI systems can handle unstructured data (e.g., social behavior, supply chain structure, and transaction paths) and predict default probabilities with higher accuracy than traditional statistical models, and that the natural language processing, sentiment recognition, and reinforcement learning capabilities of AI models can dynamically adjust risk weights to make credit decisions more responsive and flexible. The high accuracy of these assessments makes banks more willing to change their credit policies to support a group of firms rated by the AI as having 'high-quality potential'. Nallakaruppan et al. (2024) build a credit risk management system for P2P platforms based on explanatory AI models. They used Random Forest and Decision Tree models, combined with explanatory mechanisms such as LIME and SHAP, and successfully improved model transparency and prediction accuracy (up to 93%). The study shows that the AI system excels in accurately quantifying key influencing factors, improves the interpretability of policy formulation, and enhances regulatory compliance and banks' risk tolerance, thus indirectly promoting more lenient lending conditions. Gao et al. (2021) propose a multi-model system based on soft-voting integrated learning to improve the accuracy of credit risk assessment for SMEs in China. The model fused multiple algorithms such as logistic regression, SVM, random forest, XGBoost and LightGBM, which significantly improved the prediction accuracy compared to a single model. The study highlights that model fusion not only improves accuracy, but also enables banks to identify 'false positives' and 'false negatives' more comprehensively in practical credit applications, thus effectively adjusting credit policies for different groups of firms, and enhancing the precision of policy stratification. Girase's (2024) study focuses specifically on SME credit risk modeling, and develops a credit scoring system with significantly improved accuracy through decision trees, neural networks and other methods. It was found that the AI model dynamically adjusts feature weights and exhibits high stability in a multi-source data environment. Because of its 'robustness' under high accuracy conditions, AI assessment has become a core parameter in the bank's credit risk pricing system, which also strengthens the explanatory power of the independent variable on the dependent variable.

Relationship between firms creditworthiness and observed variables

Kim, J., & Park, S. (2020) argued that a firm's financial health directly affects its credit rating, and that firms with good financial health usually obtain a higher credit rating, which improves their ability to raise finance in the supply chain.

Xu, H., & Li, M. (2021) argued that a firm's performance ability is directly related to its credit risk, and firms with strong performance ability can reduce their credit risk and improve their credit rating in the supply chain.

Zhao, W., & Guo, Y. (2019) argued that a good market reputation not only helps firms to establish a solid position in the market, but also improves their credit standing, which enhances their credit performance in the supply chain.

Liu, Y., & Zhang, Q. (2022) argued that firms with higher supply chain status are usually able to control more supply chain resources, so they have lower credit risk and can obtain better financing terms and higher credit ratings.

It can be seen that, according to the current research of scholars in various countries, enterprise financial health, performance ability, market reputation, and supply chain status constitute the influencing factors of enterprise credit status. In this paper, the four indicators of enterprise financial health, performance ability, market reputation and supply chain status are the observation points of the independent variable enterprise credit status, which has the basis of theoretical support.

Relationship between core business impacts and observatories

Liu, Y., & Li, X. (2020) argued that the risk management and control capabilities of core firms significantly affect their influence in the supply chain. Core firms with strong risk management capabilities can better maintain the stability of the supply chain, thus enhancing their bargaining power and market influence.

Zhang, T., & Wang, H. (2021) argued that core firms can obtain more resources and support in the supply chain by establishing a solid relationship network and enhancing their bargaining power, which in turn improves their influence in the supply chain.

Chen, J., & Zhao, L. (2019) explored the impact of market reputation and brand influence on core firms in supply chains. The results show that core firms with good market reputation and strong brand influence are more influential in the supply chain and can coordinate and manage supply chain resources more effectively.

Wang, F., & Liu, Y. (2021) pointed out that the information sharing mechanism of core enterprises can help banks better assess the business conditions of SMEs and thus optimize credit decisions.

It can be seen that, according to the current research of scholars in various countries, risk management and control ability, relationship network and bargaining power, market reputation and brand influence, and information sharing mechanism constitute the influencing factors of the impact of core enterprises. In this paper, the four indicators of risk management and control ability, relationship network and bargaining power, market reputation and brand influence, and information sharing mechanism are the observation points of the independent variable core enterprise influence, which has the basis of theoretical support.

Relationship between commercial bank perceptions and observables

Zhang, L., & Wang, H. (2020) explored how commercial banks' credit risk identification capability affects their perceptions in supply chain finance. They argued that banks with strong credit risk identification capabilities can more accurately assess potential risks in the supply chain, and thus show greater sensitivity and precision in their credit decisions.

Liu, Y., & Chen, J. (2021) argued that the financing needs assessment capability of commercial banks is crucial to their perception in supply chain finance. Efficient assessment capability enables banks to accurately identify the real financing needs of enterprises and thus develop more effective credit strategies.

Wu, X., & Zhao, L. (2022) argued that a deep understanding of supply chain credit structure could enhance the comprehensive judgment ability of commercial banks in supply chain finance, and influence their risk appetite and decision-making behavior.

It can be seen that, according to the current research of scholars in various countries, credit risk identification ability, financing demand assessment ability, and supply chain credit structure understanding constitute the influencing factors of commercial bank cognition. In this paper, the three indicators of credit risk identification ability, financing demand assessment ability, and supply chain credit structure understanding are taken as the observation variables of the mediating variable commercial bank cognition, which has the basis of theoretical support.

Relationship between commercial bank credit policies and observatories

Zhang, J., & Liu, Q. (2022) argued that commercial banks' credit approval criteria are one of the indicators of credit policy. Stricter approval criteria tend to lead to more conservative credit policies, while looser approval criteria may trigger more credit issuance.

Wang, Y., & Chen, L. (2021) argue that the setting of credit lines and maturities is one of the indicators of commercial banks' credit policies. Significant and long-term credit lines usually help to enhance the financing ability of enterprises, but may also bring higher credit risk.

Li, X., & Zhang, H. (2023) argued that interest rate and fee setting are one of the credit policy indicators for commercial banks. Higher interest rates and fees may limit the financing needs of enterprises and affect the incentives for credit extension.

Sun, R., & Yang, M. (2020) argued that guarantee and collateral requirements are indicators of commercial banks' credit policies. Effective guarantee and collateral requirements can reduce the credit risk of banks and thus influence their credit decisions and policies.

It can be seen that, according to the current research of scholars in various countries, credit approval standards, credit limit and duration, interest rates and fees set, guarantee and collateral requirements constitute the influencing factors of commercial bank credit policy. In this paper, the four indicators of credit approval standard, credit limit and term, interest rate and fee setting, guarantee and collateral requirements are the observed variables of the dependent variable commercial bank credit policy, which has the basis of theoretical support.

Other Relevant Studies

In addition to the above studies, other studies relevant to this paper are trade credit studies, cross-border supply chain finance studies and blockchain studies.

Trade credit research. Trade on credit is a trade in which the seller delivers goods to the buyer and the buyer pays for the goods over some time after receiving the goods. Fabbri, D., & Klapper, L.F. (2023) found that core firms can significantly influence the acquisition of trade credit due to the negotiating advantage they have over firms upstream and downstream of the supply chain. Wang, J., & Zhou, L. (2023) found that Wang, J., & Zhou, L. (2023) found that the development of trade credit can promote the development of firms in emerging markets due to the imperfections of financial markets, & Zhang, X. (2024) investigated the relationship between the digitization of Chinese firms and the availability of trade credit and found that the Chinese firms' Li, Y., & Chen Li, Y., & Chen, Y. (2024) argued that supply chain finance innovations in the post-epidemic era have facilitated the development of credit and trade, and eased the liquidity pressure on small and medium-sized enterprises (SMEs). Gao, L., & Sun, H. (2024) found that trade credit plays a vital role in maintaining the stability of the supply chain and the survival of enterprises. Survival.

Cross-border supply chain finance. Cross-border supply chain finance refers to the financial services provided by financial institutions for the purpose of optimizing the overall operation of international supply chains, reducing the cost of financing, and improving the efficiency of capital use through the integration of cross-border logistics, information flow, and capital flow. J., & Zhang, Y. (2023) argued that blockchain technology provides can provide transparency and financing efficiency in cross-border transactions. Wang, L., & Sun, Z. (2023) argued that appropriate risk management measures could reduce credit risk and exchange rate risk in cross-border transactions. L., & Sun, Z. (2023) argued that appropriate risk management measures can reduce credit risk and exchange rate risk in cross-border transactions. Zhao, X., & Li, P. (2024) argued that digital technology can significantly improve the efficiency and transparency of cross-border supply chain finance. Gupta, S., & Wang, J. (2024) found that fintech can significantly improve cross-border supply chain financial services.

Blockchain. Blockchain refers to a decentralised consensus mechanism that allows multiple participants to securely record and share transaction data, where each block includes its transaction information and is linked to another block through cryptography, forming a chain that is mended and tamper-proof. D., Mann, A., & Dugan, B. (2023) found that blockchain technology can allow supply chain blockchain technology can enable real-time sharing of all aspects of the supply chain, reduce information asymmetry, and improve supply chain efficiency. Chang, S. E., & Chen, Y. (2023) found that blockchain can make the supply chain more transparent and traceable, and promote the stable development of the supply chain.T., & Acton, T. (2024) stated that in addition to improving the transparency and efficiency of the supply chain, the Blockchain can also facilitate business and commerce. Francisco, K., & Swanson, D. (2024) argue that while Blockchain can improve supply chain transparency and efficiency, there are still technical and managerial challenges.

In summary, the prediction accuracy of the AI assessment system has an amplifying and moderating effect on credit policy making. Only when the AI system has sufficient judgement accuracy and interpretability can its output be adopted by banks and further transformed into actual policies such as credit relaxation, interest rate preference or loan amount adjustment. This regulating path has become an essential embodiment of AI intervention in bank credit logic.

Table 2.1 Summary table of relevant literature

Relevant Theory	Author's Name	Year of Publication	Core Views
Information asymmetry theory	Moro, A	2019	Borrower-initiated disclosures are more favorable to the chances of obtaining a bank loan.
Relationship Lending Theory	Elsas, R	2021	Relationship lending can help commercial banks obtain more comprehensive information and make it easier for companies to get loans.
Group Lending Theory	Cull, R	2023	Group lending can diversify commercial bank credit risk
Supply finance theory	Zhao, X	2024	Supply chain finance has specific risks, and a network-based risk assessment and control method is proposed
The relationship between SME credit and commercial bank credit policy	Li, Wei	2021	Banks can better assess the credit risk of SMEs through credit rating models

Table 2.1 (Continued)

Relevant Theory	Author's Name	Year of Publication	Core Views
Relationship between core business impact and commercial bank credit policy	Li Ming	2021	The creditworthiness and market influence of core firms can enhance banks' confidence in supply chain SMEs' credits
The relationship between SME credit and commercial bank perceptions	Li Wei	2021	Banks' perception of SMEs' credit directly determines their credit risk assessment and lending decisions.
The Relationship Between Core Firm Influence and Commercial Bank Perceptions	Liu, Fang	2021	Banks usually rely on the credit information of core enterprises to assess the credit risk of SMEs in the supply chain
The relationship between commercial bank perceptions and commercial bank credit policies	Li, X	2021	Commercial banks' perceptions of supply chain risks and opportunities significantly influence the direction and strength of their credit policies.
Relationship between firms' creditworthiness and observed variables	Kim, J	2020	The financial health of a business has a direct impact on its credit rating
Relationship between core business impacts and observatories	Liu, Y	2020	Core firms' risk management and control capabilities significantly affect their influence in the supply chain

Table 2.1 (Continued)

Relevant Theory	Author's Name	Year of Publication	Core Views
Relationship between commercial bank perceptions and observables	Zhang, L	2020	Banks with strong credit risk identification can more accurately assess potential risks in the supply chain
Relationship between commercial bank credit policies and observatories	Zhang, J	2022	Commercial banks' credit approval criteria are one of the indicators of credit policy
Trade Credit Study	Fabbri, D.	2023	Heartland firms can significantly influence access to trade credit due to their negotiating advantage over firms upstream and downstream in the supply chain
Cross-border Supply Chain Finance	Zhao, X	2024	Digital technology can significantly improve the efficiency and transparency of cross-border supply chain finance
blockchain	D., Mann, A	2023	Blockchain technology can enable supply chain Blockchain technology can allow real-time sharing of all parts of the supply chain

Chapter 3
Research Methodology

To study the relationship of supply chain credit's influence on commercial banks' credit decisions, data was collected and analyzed. The researcher's working procedures included: research format, target population, sample selection, research tools, instruments, quality checks, data collection, protection of the sample group's rights, and statistical methods used to analyze the data, with the details of each question as follows:

1. Population/sample group
2. Research Instrument
3. Data collection
4. Statistical data for data analysis

The Population and the Sample

1. The Population

The official website of the China Financial Supervision and Administration Bureau (CFSA) shows that as of 31 December 2023, the total number of commercial banks in China totals 1,833 in total. Among them, there are 6 large state-owned commercial banks, 12 joint-stock commercial banks, 125 city commercial banks, 19 private banks, 41 foreign banks and 1,630 rural commercial banks.

These banks, with a total workforce of about 4 million people, are the direct formulators, implementers and perceivers of credit policy and have the most direct experience and perspective on using AI technology in the credit sector. Considering the enormous size of the commercial banking system and the high mobility of the practitioners, a census of the entire population is not feasible in practice. Therefore, this study adopts a scientific sampling method to select a representative sample from this huge population to ensure the reliability and validity of the findings. The sample will be selected with due consideration of the diversity of multiple dimensions, such as bank type, geographic region, and practitioner experience, to comprehensively reflect the current status and trends of Chinese commercial banks in the application of AI credit assessment. Specific data are shown in Table 3.1.

Table 3.1 List of Legal Persons in China's Banking Financial Institutions

Type of bank	Number of banks	Number of practitioners
Large state-owned commercial banks	6	——
Joint-stock commercial banks	12	——
city commercial bank	125	——
private bank	19	——
foreign bank	41	——
Rural commercial banks	1630	——
Total	**1833**	**Approximately 4 million**

Source: China Financial Supervisory Authority

2. Sample Groups

1) Sampling of the number of commercial banks

In this paper, sample size formula and proportional stratified sampling were proposed according to Cochran, W.G. (1977). This study focuses on 317 commercial banks from 1833 commercial banks in China.

$$n = \frac{N \times Z^2 \times p \times (1-p)}{(N-1) \times E^2 + Z^2 \times p \times (1-p)}$$

n = sample size, N = overall size, Z = Z-value (in this paper taken as 1.96 corresponding to the Z-value corresponding to the target 95% confidence level), p = hypothetical overall proportion (0.5 was used to give the maximum sample size), and

E = permissible margin of error (in this paper sampling was done with a target of 5% error).

2) Sample proportion of commercial banks

Purposive sampling was selected due to its suitability in targeting banking professionals with direct experience in credit assessment, ensuring that the responses captured expertise relevant to AI-driven supply chain finance. This study adopts a combination of Purposive Sampling (PS) and multi-stage sampling to construct the sample group. The entire sampling process is rigorous and systematic, covering the typical characteristics of the Chinese banking industry at different levels and regions, so as to obtain a sample that is highly representative of the overall situation.

In terms of the selection of bank types, to ensure that the sample is representative of the industry, this study covers the six main types that make up the bulk of China's banking sector. Specifically, these include: large state-owned commercial banks, joint-stock commercial banks, urban commercial banks, rural commercial banks, emerging private banks, and foreign banks operating in China. This choice ensures that the sample reflects the differences in strategies and practices of banks with different ownership structures, organizational sizes, market positioning and business models when confronted with AI technologies. Large state-owned banks may have an advantage in system development and data accumulation, while private and foreign banks may be more flexible in business model innovation and technology adoption.

In the final selection of respondents, this study targeted professionals directly involved in credit business decision-making and execution. Employing an electronic questionnaire as the primary method, supplemented by offline distribution, the survey was disseminated through professional networks and credit industry associations to credit practitioners across the aforementioned six categories of banks in the target cities. Key participants included deputy bank managers overseeing credit operations, heads of credit departments, credit approval officers, and personnel responsible for supply chain finance activities. During questionnaire collection, reliance on internal commercial banks and industry associations necessitated careful consideration of positional bias and social desirability effects, leading to the exclusion of invalid responses. Regarding positional bias, deputy bank managers and approval heads constituted nearly 60% of respondents, while frontline client managers were underrepresented. This composition risks amplifying a "senior management perspective" while overlooking operational challenges faced by frontline staff. Regarding social desirability bias, questionnaires distributed under banking association endorsement may have prompted respondents to present more positive attitudes towards AI adoption and compliance, potentially underestimating actual resistance and moral hazard. Ultimately, this study distributed 450 questionnaires. Following screening and collation, 360 valid responses were obtained, yielding a high effective recovery rate of 80%. This sample size not only meets the fundamental requirements for structural equation modelling (SEM) analysis but also provides a robust and reliable foundation for subsequent data analysis and hypothesis testing due to its balanced composition. Detailed demographic characteristics of the sample population will be presented in Chapter 4.

Proportionate sampling of different types of commercial banks based on proportional stratified sampling method proposed by Cochran, W.G. (1977). The sample size was calculated using the following formula:

$$n_i = \frac{N_i}{N} \times n$$

ni = number of samples in stratum i, Ni = number of totals in stratum i, N = total number of totals, n = total sample size

Table 3.2 Sample Data on Commercial Bank Schemes by Type of Bank

Type of bank	Number of banks	Sample size (5 to 20 percent)
Large state-owned commercial banks	6	1
Joint-stock commercial banks	12	2
City Commercial Bank	125	22
Private bank	19	3
Foreign bank	41	7
Rural commercial banks	1630	282
Total	**1833**	**317**

3) Number of questionnaires

This paper is based on the proposal according to Lindeman, Merenda & Gold, (1980) that the sample size for multivariate data analysis should be at least 20 times the number of parameters (variables) to be estimated. A total of 360 people were sampled. It is planned to select the vice president in charge of credit business, head of credit business department and supply chain finance business related personnel of each commercial bank from among the 293 commercial banks in the sample to cooperate in the survey. Multivariate data analysis of the sample size does publicize is:

n=N*20

n is the sample size taken and N is the number of variables.

4) Urban sampling

In terms of city selection, this study strategically selected five representative cities for the survey to ensure comprehensive coverage in terms of geography and economic development level. These five cities are: Beijing and Shanghai, as China's national financial centers, which are not only densely populated with financial institutions, but are also at the forefront of fintech and AI applications, representing the highest level of development of AI credit assessment technology; Guangzhou and

Shenzhen, as the two major regional financial hubs in South China, with a high degree of marketisation and vibrant financial innovations, which are reflective of developed market environments where bank adoption dynamics; and Nanning, as a regional Center city in Southwest China, whose sample can reflect the unique situation and challenges of banks in areas where economic development is relatively lagging behind or in the catch-up stage. With such a city layout, this study can capture differential information across the regional gradient from leading to catching up.

It is planned to sample no less than 30 samples from each city, of which 120 data samples were taken from Nanning, and 60 samples were taken from Beijing, Shanghai, Guangzhou and Shenzhen, totaling 360 samples. Specifically as shown in Table 3.3.

Table 3.3 Sampling plan by city

City Name	Sample Size
Nan Ning	120
Beijing	60
ShangHai	60
Guangzhou	60
Shenzhen	60
Total	**360**

Research Instruments

A combination of quantitative and qualitative research was carried out on the study of factors influencing SME credit in commercial banks. There were two data collection tools: 1) In-depth interviews 2) Questionnaire survey.

1. In-depth interviews

Used to collect data from 10 experts (listed in Appendix A)

2. Questionnaire survey

Used to collect data on commercial bank credit practitioners.

The steps to create the questionnaire and interview schedule are as follows:

1. Data were collected through data analysis of printed documents, books, articles, and newspaper interviews.

2. 30 people from the interview team: 30 people were interviewed from the commercial banks' SME credit business practitioners (as listed in Appendix A) The results of the interviews were analyzed and summarized as a guide for setting up the quantitative questionnaire, as shown in Table 3.4:

Table 3.4 Expert Interviews

Master	Qualifications	Quorum
Commercial bank SME credit practitioners	Heads and employees of credit departments of commercial banks	30
	Total	**30**

As can be seen from Table 3.4, a total of 30 experts in SME credit operations of commercial banks were designated, who are well equipped with the theoretical and practical conditions of commercial banking business subjects and are able to provide support for the qualitative research of this paper.

Table 3.5 Structure of the in-depth interviews

Variable	Number of Verses
Part 1 Small and Medium Enterprise Credit	
1. Financial health	3
2. Compliance	3
3. Market reputation	3
4. Supply Chain Status	3

Table 3.5 (Continued)

Variable	Number of Verses
Part 2 Core business influence	
1. Risk management and control capabilities	3
2. Relationship network and bargaining power	3
3. Market reputation and brand influence	3
4. Information-sharing capacity	3
Part 3 Commercial Banking Perceptions	
1. Credit risk identification capability	3
2. Financing needs assessment capacity	3
3. Supply Chain Credit Structure Understanding	3
Part 4 Commercial bank credit policy	
1. Credit approval criteria	3
2. Loan amount and term	3
3. Rate and Fee Setting	3
Total	**42**

3. Determine the benefits that can be gained through organizational questionnaire surveys that are consistent with the research objectives. As shown in Table 3.6:

Table 3.6 Structure questionnaire

Variable	Number of verses	Clause	Data	Measurement
Part 1				
Small and Medium Enterprise Credit	16	12		
1. Financial health	(4)	1-4	Likert Scale	5 opinion levels
2. Compliance	(4)	5-8	Likert Scale	5 opinion levels
3. Market reputation	(4)	9-12	Likert Scale	5 opinion levels
4. Supply Chain Status	(4)	13-16	Likert Scale	5 opinion levels
Part 2				
Core business influence	16	16		
1. Risk management and control capabilities	(4)	17-20	Likert Scale	5 opinion levels
2. Relationship network and bargaining power	(4)	21-24	Likert Scale	5 opinion levels
3. Market reputation and brand influence	(4)	25-28	Likert Scale	5 opinion levels
4. Information-sharing capacity	(4)	29-32	Likert Scale	5 opinion levels
Part 3				
Commercial Banking Perceptions	12	12		
1. Credit risk identification capability	(4)	33-36	Likert Scale	5 opinion levels
2. Financing needs assessment capacity	(4)	37-40	Likert Scale	5 opinion levels
3. Supply Chain Credit Structure Understanding	(4)	41-44	Likert Scale	5 opinion levels
Part 4				
Commercial bank credit policy	12	12		
1. Credit approval criteria	(4)	45-48	Likert Scale	5 opinion levels
2. Loan amount and term	(4)	49-52	Likert Scale	5 opinion levels
3. Rate and Fee Setting	(4)	53-56	Likert Scale	5 opinion levels
Total	**56**			

4. Proceed to create questions based on in-depth interviews with experts, along with studying, researching, and working on definitions then taking them to the advisor to consider and verify the appropriateness of the questions. The language used and typing formatting along with bringing improvements and corrections.

5. The completed questionnaires were given to experts for measurement and evaluation to check content validity. The expert panel consisted of a group of three people, including a statistician from a Chinese university, a reputable university professor from a Thai university, and a credit policy maker from a Chinese commercial bank, who worked together to check that the security matched the accuracy and consistency of the content coverage and language.

+1 means that you are sure that the questions are consistent with the research objective.

0 means you are unsure whether the question is consistent with the research objective.

-1 means that you are certain that the questions are inconsistent with the research objective.

The selection of question items uses criteria to judge content validity, which specifies that the calculated IOC index value must be greater than 0.6 (IOC>0.6) (Kanlaya Wanichbancha, 2009). It is therefore considered that the question items are consistent with the message to be measured.

Table 3.7 IOC content validity examiner (item objective congruence)

Experts	Experts Qualification	Number (person)
Statistical measurement and assessment experts in China	PhD, Professor in Statistics	1
Knowledge and Competence Scholars at Thai Universities	PhD Supervisor, Bansomdejchaopraya Rajabhat University	1
China's commercial banks' credit formulators	Designated Head of Credit Policy, People's Bank of China	1
Total		**3**

6. The researcher brings a draft questionnaire edited by a qualified person. presentation of advisors considers the completeness again and bring it to the trial (try-out) with a group of people who are like the sample you want to study 30 people, then bring it to the reliability value. (Cronbach's alpha coefficient).

7. The researcher brings the defects from the experiment to the final improvement, to be printed as a complete questionnaire used to collect data for research.

Scoring Criteria

The questionnaire is a study of the level of opinion about the SME credit business of commercial banks. The questions of the questionnaire are characterized by a Likert 5-level estimation scale and the meaning of the scores is as follows:(Likert Scale)

Score level 5 means the highest level of agreement.

Score level 4 means high level of agreement.

Score level 3 means moderate level of agreement.

Score level 2 means low level of agreement.

Score level 1 means the least level of agreement.

The criteria for interpreting the average scores of the observed variables are divided into five levels as follows.

Average score 4.50 – 5.00, highest level

Average score 3.50 – 4.49, high level

Average score 2.50 – 3.49, moderate level

Average score 1.50 – 2.49, low level

Average score 1.00 – 1.49, lowest level

The reasons for setting such rules are as follows:

1. The calculated arithmetic mean can be any value in the range 1-5, such as 1.75, 4.50...., 5.00.

2. The score level 1-5 is a continuous value represented by a straight line. And can be defined as a continuous scoring range which is represented by a straight line and can be defined as a continuous scoring range Each period is separated by 1 unit as follows:

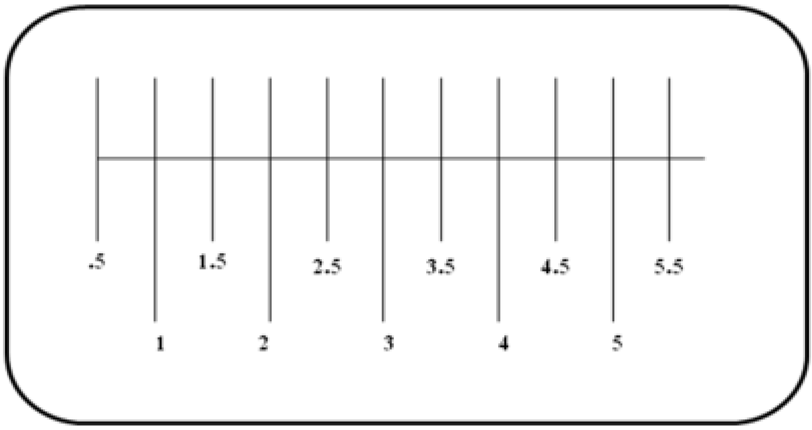

Figure 3.1 Mean Interpretation Interval Determination

Source. From William Petty

3. Based on the actual data collected from the scores The minimum value is 1 and the maximum is 5, so use the criterion 1.00 – 1.50 instead of .50 – 1.50 and use the criterion 4.50 – 5.00 instead of 4.50 – 5.50.

4. In the case where the calculated arithmetic mean ($\overline{X}$) has a value corresponding to the interval between the levels the opinions to be interpreted are at a higher level of opinion. For example, the arithmetic mean = 4.50 will mean that there is the highest level of opinion on that matter, etc.

Determining the quality of research tools

To get quality tools The researcher therefore brought a questionnaire that was created. Go test for validity and reliability. (reliability) as follows.

1. Determination of validity The researcher will check the content validity of each text to ensure that it meets the objectives of the study. By consulting with five subject matter specialists to examine the clarity of language, wording, and accuracy in the content Consistency of the questions in the questionnaire with the objectives (index of item objective congruency--IOC), with the following scoring criteria:

+ 1 when the expert or expert is sure that the question is consistent with the content.

0 When the expert is unsure whether the question is consistent with the content.

-1 when the expert or expert is sure the question is inconsistent with the content.

follow formula $IOC = \frac{\sum R}{N}$

IOC Instead, it indexes the consistency between queries. With research objectives

$\sum R$ Instead, the sum of the opinions of experts or experts.

N Instead, of the number of experts or experts.

Calculation of the consistency index between questionnaires. with research objectives Must have an Index of Conformity (IOC) value greater than 0.6. It can be concluded that the questionnaire content accuracy is within acceptable criteria. Can be used to collect further data.

2. Reliability was determined using a questionnaire validated by an advisory committee. Before using the questionnaire with the sample group, experts with specialized knowledge had modified and tested (piloted) the questionnaire on 56 test recipients with similar characteristics to the sample group to be studied. Sentiment (reliability) was analyzed using Cronbach's (1990) Alpha coefficient method. If the reliability coefficient is greater than 0.8 (Kanlaya Wanichbancha, 2008), the questionnaire is reliable and can be used in the study.

The data collection tool at the center of this paper was a structured questionnaire. The questionnaire was designed in a rigorous process to accurately measure each of the core constructs in the framework of this study. The entire development process was based on borrowing and adapting existing well-established scales and closely aligned with the unique context of this study - i.e., the application of Artificial Intelligence (AI) in supply chain credit assessment. To ensure the applicability and forward-looking nature of the questionnaire, the study began with an extensive literature review and in-depth interviews with 10 senior credit business experts from different types of banks, the results of which provided invaluable practical insights and theoretical basis for the initial construction of the questionnaire items.

The main body of the questionnaire is divided into two parts. The first section contains basic information about the respondents, including the type of bank they work for, their geographical location, their position, and the number of years they have worked in credit-related jobs. These demographic variables will be used as control variables in subsequent analyses to exclude potential confounders and enhance the robustness of the study findings.

The second part is the measurement scale of the core concepts, which covers all the independent, mediating, moderating and dependent variables of this study. All measurement items were scored on an internationally accepted 5-point Likert scale, with '1' to "5" representing "Strongly Disagree ', 'Disagree', 'Neutral', "Agree", and 'Strongly Agree ". This design facilitates respondents to express the nuances of their attitudes, and also enables the subsequent quantitative statistical analyses. The detailed structure of the questionnaire and the distribution of questions are shown in Table 3.8.

Table 3.8 Questionnaire structure and distribution of questions

Variables (Concepts)	Sub-dimension/measurement direction	number of questions
Creditworthiness of SMEs (SCS)	Business stability, repayment history, financial transparency, etc.	5
Core Corporate Influence (CEI)	Reputation, payment reliability, supply chain position, etc.	5
Artificial Intelligence Enhanced Banking Cognition (CBAEC)	Data Processing, Pattern Sensing, Decision Confidence, etc.	5
Artificial Intelligence Assessment Accuracy (AAA)	Algorithm accuracy, system reliability, error rate, etc.	5
Commercial Bank Credit Policy (CBCP)	Approval rate, amount, interest rate, efficiency, etc.	5

2.1 Pretest and Reliability Analysis

After content validity was assured, a pre-test (Pilot Study) was conducted to test the reliability and preliminary structural validity of the questionnaire. Thirty commercial bank credit practitioners who did not participate in the formal survey but whose characteristics were similar to the target sample were selected to complete the questionnaire for this study. After collecting the pre-test data, this study used SPSS software to analyze the internal consistency of each construct for reliability, mainly using Cronbach's Alpha coefficient (Cronbach's alpha) as a measure. The results of the reliability analysis are the key to measuring the stability and reliability of the questionnaire, and an Alpha coefficient greater than 0.7 is usually considered an acceptable level. The results of the reliability analysis of the pre-test in this study are shown in Table 3.9, where the Alpha coefficients of all constructs are much higher than 0.8, indicating that the questionnaire has excellent internal consistency.

Table 3.9 Results of Pretest Reliability Analysis (Cronbach's α)

Variables (Concepts)	Number of questions	Cronbach's α	Reliability level
Creditworthiness of SMEs (SCS)	5	.885	Favorable
Core Corporate Influence (CEI)	5	.861	Favorable
Artificial Intelligence Enhanced Banking Cognition (CBAEC)	5	.892	Excellence
Artificial Intelligence Assessment Accuracy (AAA)	5	.879	Favorable
Commercial Bank Credit Policy (CBCP)	5	.903	Excellence
Overall questionnaire	**25**	**.948**	**Excellence**

2.2 Structural validity tests

Structural validity is used to test whether the measurements of a questionnaire truly reflect the structural relationships of the theoretical constructs behind it. In this study, a detailed structural validity test will be conducted on the 360 formally collected data through Confirmatory Factor Analysis (CFA) in the data analysis section of Chapter 4. CFA analysis will assess the degree of fit of the measurement model to the actual data. The leading indicators examined include chi-square degrees of freedom (χ^2/df), root mean square of the approximation error (RMSEA), comparative fit index (CFI), Tucker-Lewis Index (TLI) and the Square Root (RMSEA), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI) and Standardized Residual Mean Square Root (SRMR). The study will also assess the convergent validity of the constructs by calculating the average variance extracted (AVE) and test the discriminant validity by using the Fornell-Larcker criterion and the heterogeneitymonomorphism ratio (HTMT) to ensure that the questionnaire is structurally robust and valid.

Data Collection

Overall assessment of SMEs' corporate credit interviews

1. Strategies and processes for data collection

The data collection of this study followed a systematic, multi-channel and rigorous implementation strategy to ensure the acquisition of high-quality and representative primary data to lay a solid foundation for the subsequent empirical analysis. The entire data collection process lasted four months from March 2024 to June 2024. It was divided into three core phases: questionnaire distribution, data recovery and tracking, and preliminary collation and coding.

During the distribution phase of the questionnaire, the study used a combination of channels to maximize the reach to the target respondents. The primary distribution methods were through professional networks and several regional credit industry associations with which this study has established co-operative relationships. An electronic invitation with a link to the questionnaire was sent to its members, namely commercial banks located in the five target cities of Beijing, Shanghai, Guangzhou, Shenzhen and Nanning. The invitation letter detailed the academic purpose of the study, the principle of anonymity, and the potential contribution to industry practice to increase respondents' willingness to participate. Also, in order to reach banks or sectors that are difficult to get through formal channels, members of the research team used their personal academic and industry contacts to personally contact and invite eligible credit professionals to participate in the survey.

2. Data recovery and quality control

Data recovery and quality control are a crucial part of the whole data collection process, which is directly related to the validity of the data eventually used for analysis. This study set a target distribution size of 450 in total, with a view to obtaining more than 360 valid samples after taking into account invalid questionnaires and non-responses, to meet the requirements of structural equation modelling analysis. Two weeks after the distribution of the questionnaires, the study initiated the first round of collection and tracking procedures. The research team monitored the progress of questionnaire retrieval through the back-end system and sent polite reminder emails to respondents who had been distributed but had not yet responded, re-emphasizing the significance of the study and thanking them for their support.

Throughout the retrieval period, this study conducted a rigorous preliminary screening of each submitted questionnaire to eliminate invalid data and ensure data quality. The screening criteria for invalid questionnaires mainly included: first, the response time was too short. For example, samples that completed the questionnaire in much less than the normal range of reading and thinking time were regarded in this study as possibly not having answered the questionnaires carefully; second, there was a clear regular pattern of responses, for example, choosing the same option for all the questions (e.g., selecting all '5' or '3'); and third, there was a significant amount of missing key demographic information or core scale items. After such rigorous screening, this study eliminated the unqualified portion from the recovered questionnaires. Eventually, this study obtained 360 complete and valid questionnaires, with a valid recovery rate of 80.0%, as shown in Table 3.10 for the distribution and recovery of the questionnaires.

Table 3.10 Statistics on Distribution and Return of Questionnaires

Items	**Quantity (copies)**	**proportions**
Number of questionnaires planned for distribution	450	100%
Number of questionnaires returned	382	84.9%
Number of invalid questionnaires	22	4.9%
Final number of valid questionnaires	360	80.0%

3. Data coding and entry

Immediately after confirming that 360 valid questionnaires were obtained, this study initiated data coding and entry, a critical step in transforming the raw questionnaire information into standardized data that can be analyzed by statistical software. Firstly, this study set unique numerical codes for each variable and option in the questionnaire. For the five-point Likert scale items of the core scale, the codes were consistent with the scores, i.e., from '1' to "5" representing 'strongly disagree' to 'strongly agree' respectively. 'Strongly Agree'.

This study also digitally coded the categorical variables in the demographic section. For the 'bank type' variable, the study coded 'large state-owned commercial banks' as '1', 'joint-stock commercial banks' as "2", and so on up to 'foreign banks' as '6'. '2' and so on until "6" for 'foreign banks'. Similarly, variables such as geographic location, position, and years of experience were assigned numerical codes. The specific coding scheme is shown in Table 3.11.

Table 3.11 Some demographic variable coding schemes

Variable Name	Category/Options	Coding
Bank Type	Large state-owned commercial banks	1
	Joint-stock commercial bank	2
	City Commercial Bank	3
	Rural Commercial Bank	4
	Private Bank	5
	Foreign-funded banks	6
Location	Beijing	1
	Shanghai	2
	Guangzhou	3
	Shenzhen	4
	Nanning	5

After all coding work was completed, this study entered the data of these 360 valid questionnaires into the SPSS (Statistical Package for the Social Sciences) 26.0 software one by one, forming a standardized data file. To ensure the accuracy of data entry, this study also conducted a secondary check, that is, another researcher randomly selected 10% of the samples (36 questionnaires) for independent entry and compared them with the original entered data. The comparison results show that the consistency is 100%.

Data collection from in-depth interviews

Because this in-depth interview will use both interviews and conversation recordings using a voice recorder. Therefore, data collection used both interview recordings and recordings in the memory of the voice recorder. Then open it to transcribe into a recording later again with the following steps.

1. Schedule an interview with an expert by notifying him in advance.

2. Interview according to the structure and record it in the recording form. Including voice recordings during the interview

3. Bring all the information to compose and transcribe completely from the voice recorder. according to the content structure designed in the interview form, including additional useful things received from the interview.

4. Analyze the data using content analysis techniques and summarize the interview results into descriptive data.

In-depth interviews with practitioners in the credit departments of commercial banks are summarized below:

Overall assessment of SMEs' corporate credit interviews

When assessing the creditworthiness of SMEs, commercial banks take into account four aspects: financial health, performance ability, market reputation and supply chain position. Supply chain credit plays an important role in this, especially by influencing the financial health, performance capability and market reputation of an enterprise, which ultimately affects credit decisions. Experts argued that improving these aspects of creditworthiness, especially the position in the supply chain, could significantly improve SMEs' chances of obtaining credit.

Financial health. During the interviews, experts agreed that the financial health of SMEs is a key factor influencing credit decisions. Interviewees pointed out that the completeness of financial statements, the stability of cash flows, and the balance sheet structure of the enterprise had a direct impact on the approval rate of its loan applications. Many managers mentioned that financial health not only reflects the current financial strength of an enterprise, but also predicts its future solvency. Therefore, when assessing credit risk, banks pay particular attention to core financial indicators such as SMEs' revenue growth trends, net profit margins, and current ratios. In addition, interviewees emphasized that the quality of supply chain credit indirectly affects the financial health of an enterprise. Stable supply chain partnerships can reduce financial uncertainty and improve the operational stability of an enterprise, thereby enhancing its creditworthiness in the eyes of banks.

Ability to perform. Performance capability is another important dimension for banks to assess the creditworthiness of SMEs. During the interviews, experts agreed that performance capability is not only reflected in the execution of contracts, but also involves the flexibility of enterprises to cope with unforeseen situations and their ability to perform consistently. Several interviewees mentioned that when assessing the performance capacity of SMEs, banks usually refer to the historical performance record of the enterprise, customer feedback, and cooperation evaluation of supply chain partners. It is worth noting that the assessment of SMEs' performance capability by core enterprises in the supply chain plays a vital role in banks' credit assessment. If the core firms rate the performance of SMEs positively, banks tend to be more willing to offer more favorable credit terms. Conversely, if performance is poor, banks may adopt more cautious credit policies.

Market reputation. Market reputation was widely recognized in the interviews as an essential component of the creditworthiness of SMEs. Experts pointed out that a good market reputation can reduce a firm's credit risk and increase the likelihood of obtaining loans. Interviewees mentioned that the market reputation of core firms in a supply chain often has a significant impact on SMEs throughout the supply chain. If SMEs have a close working relationship with core enterprises with a high market reputation, banks usually perceive these enterprises as having lower credit risk and are therefore more willing to provide them with credit support. Conversely, if the market reputation is poor, banks may be more conservative in granting credit.

Supply chain position. Interviews revealed that the position of SMEs in the supply chain directly affects their creditworthiness in the eyes of banks. Experts agreed that firms at the core of the supply chain usually had stronger bargaining power and more stable market demand, factors that made banks more inclined to provide credit support when assessing credit risk. It was also mentioned in the interviews that the stability and transparency of the supply chain also affected the supply chain position of SMEs. Those with strategic partners or occupying essential nodes in the supply chain tend to be regarded as low-risk customers by banks. Therefore, the higher the supply chain status of an SME, the more likely it is to receive credit support from banks.

Overall assessment of core business impact

Overall, when assessing the impact of supply chain credit on SMEs' credit policies, commercial banks pay special attention to the influence of core enterprises, specifically their risk management and control capabilities, relationship networks and bargaining power, as well as market reputation and brand influence. These factors not only determine the stability and impact of the core enterprise in the supply chain, but also directly affect the credit level and market position of the SMEs it cooperates with. Experts believed that SMEs working with strong core enterprises had an advantage in credit applications and that banks were more willing to provide credit support to these enterprises to reduce overall credit risk.

1. Risk management and control capacity. In the interviews, experts believed that the risk management and control capacity of core enterprises is an essential guarantee for the stable operation of supply chains. Interviewees pointed out that as a key node in the supply chain, the risk management and control capacity of core enterprises not only affects their operational stability, but also has a far-reaching impact on the risk profile of the entire supply chain. Credit managers mentioned that core enterprises with strong risk management and control capabilities can effectively

prevent and mitigate various risks in the supply chain, such as supply chain disruptions, market volatility and credit risks. This not only enhances the resilience of the entire supply chain, but also strengthens the creditworthiness of enterprises upstream and downstream of the supply chain. When assessing credit applications from SMEs, banks usually regard cooperation with core enterprises with strong risk management capabilities as an essential factor in reducing credit risks.

2. Networks and bargaining power. Networks and bargaining power are essential means for core firms to influence the supply chain. In the interviews, experts argued that strong relationship networks and bargaining power of core enterprises not only help them to occupy a favorable position in the market, but also bring greater market opportunities and resource support to SMEs in the supply chain. Interviewees pointed out that core enterprises, through their extensive relationship networks, can help enterprises upstream and downstream of the supply chain to obtain more market information and resource support, thus enhancing the synergy efficiency of the entire supply chain. In addition, the bargaining power of core enterprises can get better trading conditions in negotiations with suppliers and customers, which not only helps reduce costs but also enhances the market competitiveness of the supply chain. In their credit assessment, banks usually focus on whether SMEs are working with core firms that have strong relationship networks and bargaining power, as this can significantly reduce the operational and market risks of SMEs.

3. Market Reputation and Brand Impact. Market reputation and brand influence are another key factor of core firms' influence that experts in the interviews generally focused on. Interviewees believe that the market reputation and brand influence of core firms directly affect their position and influence in the supply chain, which in turn has a significant impact on the credit status of upstream and downstream firms. Experts mentioned that the good market reputation and strong brand influence of core enterprises can not only enhance their market competitiveness, but also bring positive reputation effect and brand endorsement to SMEs in the supply chain. This effect can enhance the market image and credit level

of the supply chain as a whole, thus reducing the risk of default and market volatility in the supply chain. When assessing credit applications from SMEs, banks will usually consider whether these enterprises cooperate with core enterprises with good market reputation and brand influence, as such a cooperative relationship usually implies lower credit risk and higher market stability.

4. Information sharing capabilities. Information-sharing capacity is another key factor of core firms' influence that was of general concern to experts in the interviews. Interviewees believe that the information-sharing capacity of core enterprises plays a crucial role in commercial banks' assessment of SME credit risk. Core enterprises with high information transparency and sound sharing mechanisms can help banks obtain more key information about the financial status and operations of enterprises in the supply chain. The effective transmission of such information not only enhances banks' trust in SMEs, but also reduces the risk of information asymmetry. Especially in supply chain finance, information sharing is an essential tool to minimize credit risk and enhance credit efficiency. Bank credit managers generally believe that SMEs that work with core enterprises with strong information-sharing capabilities can better gain banks' trust and financial support.

General Assessment of Commercial Banking Perceptions

When assessing the impact of supply chain credit on SME credit policies, commercial banks pay particular attention to the ability to identify credit risks, the ability to determine financing needs and the understanding of supply chain credit structures. These perceptions not only help banks to identify and control risks more accurately, but also improve their understanding of SMEs' financing needs, thereby optimizing the credit decision-making process. In the supply chain credit environment, banks effectively support the financing needs of SMEs through comprehensive risk identification and assessment, while reducing their credit risk.

Credit risk identification skills. During the interviews, experts emphasized the key role of credit risk identification skills in credit decision-making. Interviewees pointed out that, as SMEs are generally characterized by opaque financial information and high operational volatility, identifying their potential risks is crucial to credit decision-making. Experts mentioned that they rely on various tools and methods to assess the credit risk of SMEs, including financial statement analyses, cash flow projections, and industry risk assessments. In addition, they would also consider factors such as the economic health of the core enterprise and the stability of the links in the supply chain through the lens of supply chain credit to identify and control credit risks in a more comprehensive manner. The interviewees agreed that enhancing credit risk identification capability would help banks make more prudent credit decisions when facing SMEs with greater uncertainties.

Financing needs assessment capability. In terms of financing needs assessment, interviewees said that the first task of commercial banks is to accurately understand the financing needs of SMEs and make a reasonable assessment in conjunction with the credit status of the supply chain. Experts believe that the financing needs of SMEs are often characterized by seasonality and short-termism, and determining the real use of funds and risk points behind these needs is the core of the assessment. Credit managers of commercial banks mentioned that the performance and credit status of core enterprises in the supply chain would directly affect the financing needs of SMEs. For example, when the core enterprise is under financial stress, the entire supply chain may become strained, thus increasing the financing needs of SMEs. Banks will take these factors into account when assessing the financing needs of SMEs to ensure that the amount of credit provided matches the actual needs of the enterprises and to avoid over-credit or under-credit.

Supply chain credit structure understanding. The understanding of supply chain credit structure was another important topic discussed by experts in the interviews. Interviewees believe that supply chain credit is not only the credit status of individual enterprises, but also the credit relationship and risk transmission mechanism within the whole supply chain system. Therefore, banks need a comprehensive understanding of the supply chain credit structure to make more precise judgements when making credit decisions. Credit managers point out that they assess the credit structure of the entire supply chain by analyzing information such as the relationships between core enterprises, upstream and downstream enterprises in the supply chain, transaction patterns and contract performance. Especially in complex supply chains involving multiple SMEs and core enterprises, understanding these credit relationships and structures is critical to accurately assessing overall credit risk. Interviewees agreed that an in-depth understanding of the credit structure of the supply chain can help banks better identify and prevent potential credit risks and optimize the allocation of credit resources.

General Review of Commercial Bank Credit Policy

Commercial banks take supply chain credit into full consideration when formulating and adjusting their credit policies. Decisions on credit approval criteria, loan amount and term, interest rate and fee setting, and guarantee and collateral requirements are all significantly affected by supply chain credit. By evaluating the credit status of the supply chain, banks can more accurately formulate credit policies, which not only meets the financing needs of SMEs, but also effectively controls credit risks. In the context of supply chain credit, banks' credit policies become more flexible and precise, promoting the development of SMEs while consolidating the stability of the entire supply chain.

1. Credit approval criteria. In the interviews, experts discussed the adaptation and impact of credit approval criteria in the supply chain credit environment. Interviewees indicated that the overall state of supply chain credit has a significant effect on credit approval criteria, especially when assessing the credit risk of SMEs. Banks usually consider the credit status of the core enterprise and the overall credit structure of the supply chain and incorporate these factors into their credit assessment of SMEs. This means that if SMEs are more critical in the supply chain or the core enterprises they work with are creditworthy, banks may relax their credit approval criteria accordingly. This adjustment based on supply chain credit aims to bring about a win-win outcome for banks and SMEs by reducing credit risk.

2. Loan amount and term. Regarding loan amounts and maturities, experts in the interviews pointed out that supply chain credit played a key role in decision-making in these areas. Banks usually set the loan amount and term based on the SME's role in the supply chain and its partnership with the core enterprise.

Interviewees indicated that banks may offer higher loan amounts and more flexible maturities if SMEs occupy a more solid position in the supply chain and have a strong and stable partnership with the core enterprise. This strategy aims to support SMEs' financial liquidity and ensure that they can successfully fulfil their responsibilities in the supply chain, while also enabling banks to make efficient use of their credit resources.

3. Interest rate and fee setting. Interviews with credit managers also explored the flexibility of interest rate and fee setting. Interviewees generally agreed that supply chain credit can significantly influence the setting of interest rates and related fees for bank lending to SMEs. Specifically, if the overall creditworthiness of the supply chain is more favorable and the market performance and creditworthiness of the core firm are stronger, banks may offer more favorable interest rates and fee settings. The aim of this practice is to encourage the continued participation of SMEs in the supply chain and to reduce their financing costs, thereby enhancing the stability and competitiveness of the supply chain as a whole.

4. Statistics Used for Data Analysis

When the questionnaires were returned, the researcher manually checked all questionnaires for accuracy and completeness. The questionnaires were then coded and processed by the computer. The data were then statistically analyzed. In interpreting the meaning of all the data obtained and displaying the results, the study used content analysis, descriptive statistical analysis, and inferential statistical analysis (inferential statistical analysis).

This study adopts a systematic, multi-level quantitative data analysis method to comprehensively and in-depth test research models and hypotheses. All data analysis work will be mainly done with the professional statistical analysis software SPSS 26.0 and AMOS 24.0. The analysis process will start from the basic descriptive statistics and reliability and validity tests, gradually penetrate the core structural equation model analysis, and finally fully reveal the complex mechanism of action between variables through the test of mediating effects and regulation effects.

4.1 Descriptive statistics and preliminary tests

Before conducting complex model testing, the first step is to conduct basic description and test the sample data. This stage mainly includes two core tasks: descriptive statistical analysis and standard deviation test.

First, this study will use SPSS software to conduct frequency analysis of the demographic characteristics of the sample (such as bank type, geographical location, employment experience, etc.) to clearly show the composition and distribution of the sample and evaluate its representativeness. At the same time, descriptive statistics such as mean, standard deviation, skewness and kurtosis will be calculated for the five core concepts in the study - the credit status of small and medium-sized enterprises, the influence of core enterprises, the bank awareness enhanced by artificial intelligence, the accuracy of artificial intelligence evaluation, and the credit policy of commercial banks. These statistics can not only help understand the respondents' overall attitude tendency and degree of dispersion towards each construct, but also test whether the data meets the standard distribution assumptions required by subsequent multivariate statistical analysis, providing a basis for choosing appropriate analysis methods.

Secondly, considering that the data in this study were all collected at the same time point through the same questionnaire, there may be problems with common method bias (Common Method Bias). To evaluate and control for this potential bias, two methods will be used for the test. The first is the Harman single-factor test, which conducts exploratory factor analysis (EFA) on all measurement questions to observe the total variance explained by the first factor without rotation. If this value is well below the critical criterion of 50%, it indicates that the standard deviation does not pose a serious problem. The second is the more rigorous Common Latent Factor (CLF) method, that is, a standard method latent factor connecting all observed variables is added to the measurement model. By comparing the degree of change in model parameters before and after increasing the factor, we can judge whether the effect of deviation is significant.

4.2 Measurement Model Analysis (CFA)

After confirming the basic data situation and the absence of serious standard method deviations, AMOS 24.0 software will be used for confirmatory factor analysis (CFA) to strictly test the reliability and validity of the measurement tools of this study. CFA is the first step in the structural equation model, and its purpose is to verify whether the preset theoretical construct structure (i.e. which questions measure which latent variable) fits with the collected actual data.

In CFA analysis, the following aspects will be focused on:

Model fit: This study will use a comprehensive set of fit indexes to evaluate the goodness of fit of the entire measurement model. These indicators and their judgment criteria are shown in Table 3.12. A well-fitted model is a prerequisite for subsequent structural model analysis.

Reliability Test: This study will calculate the Composite Reliability (CR) for each construct. The CR value reflects the degree of consistency of all questions within the concept, usually requiring greater than 0.7, indicating good reliability.

Convergence validity test: This study will calculate the Average Variance Extracted (AVE) for each construct. The AVE value measures the ratio of variance that a construct can interpret through its measurements, usually requiring greater than 0.5, indicating that the measurements of the construct can effectively converge at the latent variable it represents. At the same time, this study will also test the standardized factor loading of all questions, which should ideally be greater than 0.7.

Differentiation validity test: This study will use two methods to test the distinction between different constructs. The first is the Fornell-Larcker criterion, which compares the correlation coefficient between the square root of each construct AVE value and its relationship with other constructs. The former should be greater than the latter. The second is the Heterotrait-Monotrait Ratio (HTMT) test, which should be less than the strict standard of 0.85 to prove significant differences between constructs.

Table 3.12 Evaluation criteria for fitting of structural equation models

Fit index	Symbol	Acceptable Standards	References
Chi-square degree of freedom ratio	χ^2/DF	< 3.0 (ideal< 2.0)	Kline (2016)
Approximate error root mean square	RMSEA	< 0.08 (ideal < 0.05)	Browne & Cudeck (1993)
Comparison of fit index	CFI	> 0.90	Bentler (1990)
Tucker-Lewis Index	TLI	> 0.90	Tucker & Lewis (1973)
Standardized residual root mean square	SRMR	< 0.08 (ideal < 0.05)	Hu & Bentler (1999)

4.3 Structural model analysis and hypothesis testing (SEM)

Following validation of the measurement model, which demonstrated the research instruments possessed sound reliability and validity, this study will proceed to the core hypothesis testing phase. This stage will simultaneously test all proposed hypotheses by constructing a comprehensive Structural Equation Modelling (SEM) framework. The selection of Structural Equation Modelling (SEM) for this research offers three principal advantages:

1. Multiple Mediation and Chain Mechanism

The research hypothesizes that AI applications indirectly influence SME financing constraints through a chained pathway: information transparency → risk assessment accuracy → credit rationing.

2. Control of latent variable measurement error

The core constructs in this study were measured using multi-item Likert scales, constituting latent variables subject to measurement error. SEM explicitly incorporates measurement error into equations via factor models, yielding more unbiased path estimates.

3. Overall Model Fit and Complex Relationship Characterization

Beyond path coefficients, SEM provides overall fit indices such as RMSEA, CFI, and TLI to assess the degree of alignment between theoretical models and empirical data. It also permits the specification of competing models for comparison. When confronted with complex theoretical frameworks involving latent variables, multiple mediators, and chained effects, SEM proves a more suitable analytical tool.

The hypotheses proposed in this study encompass direct effects, mediating effects, and moderating effects.

1. Direct effect and mediation effect test

This study will construct a structural model containing independent variables (SCS, CEI), mediating variables (CBAEC), and dependent variables (CBCP). Running the model through AMOS software, this study will obtain the standardized path coefficients (β values), standard errors (S.E.), and significance levels (p values) for each path. Wherein, the path coefficients of independent variables pointing to the dependent variable will be used to test the direct effect hypothesis (H1, H2).

For the test of mediating effects (H3, H4), this study will adopt the Bootstrapping (self-help method) widely recommended by the academic community. This method generates an empirical indirect effect distribution by performing repetitive sampling of the original samples thousands of times (set to 5000 times in this study), thereby calculating a more robust confidence interval. If the 95% confidence interval of the indirect effect does not contain 0, it indicates that the mediation effect is statistically significant. At the same time, this study will also observe the changes in the original direct effect path coefficient after adding the mediation variable to determine whether the mediation effect is a complete mediation or a partial mediation.

2. Regulation effect test

For the regulation effect hypothesis (H5), that is, to test whether the accuracy of artificial intelligence assessment (AAA) regulates the impact of independent variables on the dependent variable, this study will adopt two complementary methods. The first method is to build interactive terms. This study first centralized the independent variable and the moderating variable (to avoid the multicollinearity problem), and then multiplied the two centralized variables to generate interactive terms. Integrated independent variables, moderating variables, and interaction terms into the regression model, and if the coefficients of the interaction terms are significant, it indicates that the moderating effect exists.

The second method is multi-group analysis. This study will divide 360 samples into "high accuracy group" and "low accuracy group" based on the median or mean of the median variable (AAA). This study will then run the same structural model in two groups of samples and compare whether the differences in the critical path coefficients between the two groups are statistically significant. If the path coefficients of the high-accuracy group are significantly stronger than those of the low-accuracy group, the regulation effect is more strongly supported. The combination of these two methods will provide more comprehensive and robust evidence for the examination of regulatory impacts. The SEM model index is specific to 3.13.

Table 3.13 Criteria for agreeing on model conformity with empirical data.

Statistical Values	Symbols	Acceptance Criteria	Reference
Chi-square	$\chi 2$	-	
Degrees of freedom	Df	-	
Chi-square/ Degrees of freedom	$\chi 2$/df	< 2	Wu Ming Long (2013)
probability	P-Value	>0.05	
Root means square error of approximation	RMSEA	<0.05	
Comparative Harmony Index (GFA)	CFI	>0.9	Jöreskog, K. G., & Sörbom, D. (1981)
Tucker-Lewis (AGFI)	TLI	>0.9	
Square root index of standard residuals.	SRMR	<0.05	

Chapter 4
Results of Analysis

The purpose of this study is to examine the factors affecting credit to SMEs in commercial banks. The results of data analysis are presented below:

1. Symbols and abbreviations
2. Introduction to data analysis
3. Results of data analysis

The details are as follows.

Symbol and Abbreviations

Table 4.1 Symbols and descriptions

Symbols	Explain
SME	Small and Medium-sized Enterprises
CE	Core Enterprise
BC	Commercial Bank
SCF	Supply Chain Finance
α	Cronbach's Alpha
KMO	Kaiser-Meyer-Olkin
CFA	Confirmatory Factor Analysis
EFA	Exploratory Factor Analysis
SEM	Structural Equation Modeling
χ^2	Chi-square
df	Degrees of Freedom
χ^2/df	Chi-square degree of freedom ratio
p	Level of significance (p-value)
RMSEA	Root Mean Square Error of Approximation

Table 4.1 (Continued)

Symbols	Explain
CFI	Comparative Fit Index
TLI	Tucker-Lewis
SRMR	Standardized Root Mean Square Residual
AVE	Average Variance Extracted
CR	Composite Reliability
β	Standardized path coefficients
CI	Confidence Interval
SME Credit	Credit status of small and medium-sized enterprises
CE Influence	Core corporate influence
BC Cognitio	Commercial Banking Cognition
BC Credit Policy	Commercial Bank Credit Policy
ACME	Average Causal Mediation Effect
ADE	Average Direct Effect
TE	Total Effect

Introduction to data analysis

1. Descriptive statistical results

The average scores for all core variables were significantly higher than the midpoint of the scale, indicating that bank professionals had a general positive attitude towards AI-driven supply chain credit assessment and related aspects. The absolute values of skewness and kurtosis of each variable are within an acceptable range, satisfying the standard distribution assumption, providing a basis for subsequent parameter testing.

2. Relevance analysis results

There is a statistically significant positive correlation between all five core variables, and the correlation coefficients are below the critical value of 0.80, implying that the multicollinearity problem between variables is within an acceptable range, creating favorable conditions for structural equation model analysis.

3. Measurement model verification results

The five-factor measurement model is well fitted with the actual data, and all fit indexes (chi-square degree of freedom ratio, approximate error root mean square, comparative fit index, Tucker-Lewis index, and standardized residual root mean square) meet the recommended standards. The reliability indicators of each construct (Cronbach's Alpha coefficient and combination reliability) are much higher than the accepted standards, indicating that the measurement items have a high degree of intrinsic consistency and stability. At the same time, convergence and discriminative validity have also been fully verified, ensuring the quality of the measurement model.

4. Structural Model Test Results (SEM)

(1) Direct influence

The credit status of small and medium-sized enterprises and the influence of core enterprises have a significant positive impact on the credit policies of commercial banks, indicating that under the AI evaluation framework, the company's credit status and the influence of core enterprises in the supply chain are crucial to obtaining favorable credit policies. The direct effect of the influence of core enterprises is slightly higher than that of the credit status of small and medium-sized enterprises.

(2) Intermediary effect

The enhanced bank cognition by artificial intelligence plays a partial intermediary role between the credit status of small and medium-sized enterprises, the influence of core enterprises and the credit policies of commercial banks, indicating that the improvement of cognitive ability of bank practitioners with the assistance of AI is an important bridge to affect credit policies.

(3) Regulation effect

The accuracy of artificial intelligence assessment positively regulates the impact of the credit status of SMEs and core enterprise influence on commercial banks' credit policies. That is, the higher the accuracy of the AI system, the more its positive effect on the credit status of SMEs and core enterprise influence can be significantly transformed into better credit policies, highlighting the key value of high-quality AI technology in supply chain finance.

Results of Data Analysis

1. Descriptive statistical analysis results

The final effective sample of this study totaled 360, all from professionals engaged in credit-related business in China's commercial banks. To evaluate the representativeness and diversity of the sample, this study conducted a detailed frequency analysis of the demographic information of the respondents, and the specific results are shown in Table 4.2.

Regarding bank types, the sample achieves comprehensive coverage of major bank categories in China. Among them, private banks accounted for the highest proportion, at 20.56% (74 people), which may reflect that emerging private banks are more active in adopting financial technologies such as AI. Following closely behind are large state-owned commercial banks, accounting for 18.89% (68 people). As the mainstay of the industry, their views are crucial. The proportions of urban and rural commercial banks were 17.50% (63 people) and 16.94% (61 people), respectively, reflecting the extensive participation of regional financial institutions. In addition, foreign banks (13.33%) and joint-stock commercial banks (12.78%) also constitute essential components of the sample. Overall, the sample is distributed balanced in bank ownership, scale and market positioning, providing a good foundation for the universality of research conclusions.

Regarding geographical location distribution, this study covers five representative financial cities in China. Among them, the sample from Beijing accounted for 22.22% (80 people), followed by Guangzhou, accounting for 21.39% (77 people). The sample proportions in Nanning, Shenzhen and Shanghai were also above 18%, namely 19.44% (70 people), 18.61% (67 people) and 18.33% (66 people) respectively. This balanced geographical distribution allows this study to capture different practices and cognitions in the application of AI credit assessment from national financial centers to regional hub cities, avoiding the limitations of the study conclusions being limited to a specific region.

In terms of experience, the sample also shows good hierarchy. The "new generation" credit personnel with 1-3 years of experience accounted for the highest proportion, at 28.89% (104 people), and their perspective may better represent the future development trend of the industry. The backbone with 4-6 years (25.56%) and 7-9 years (23.89%) work experience constituted the main body of the sample, and their rich practical experience provided a solid realistic foundation for this study. At the same time, expert respondents with more than 10 years of senior experience also accounted for 21.67% (78 people), and their profound insights provide guarantees for the depth of research. Overall, the reasonable distribution of the samples in the empirical structure ensures that the research results can comprehensively reflect the views of practitioners with different qualifications.

Table 4.2 Sample demographic characteristics descriptive statistics (N=360)

Feature	Type	Frequency	Percentage
Bank Type	Private Bank	74	20.56%
	Large state-owned commercial banks	68	18.89%
	City Commercial Bank	63	17.50%
	Rural Commercial Bank	61	16.94%
	Foreign-funded banks	48	13.33%
	Joint-stock commercial bank	46	12.78%
Position	Deputy President in charge of credit business	100	27.78%
	other	95	26.39%
	Head of the credit department	87	24.17%
	Credit department staff	78	21.67%

Table 4.2 (Continued)

Feature	Type	Frequency	Percentage
Working years	1-3 years	104	28.89%
	4-6 years	92	25.56%
	7-9 years	86	23.89%
	More than 10 years	78	21.67%
City	Beijing	80	22.22%
	Guangzhou	77	21.39%
	Nanning	70	19.44%
	Shenzhen	67	18.61%
	Shanghai	66	18.33%

After understanding the basic situation of the sample, this study conducted a descriptive statistical analysis of the five core constructs involved to explore the respondents' overall perception of these variables and the basic distribution characteristics of the data. The specific results are shown in Table 4.3.

On average, the average scores of all core variables were significantly higher than the midpoint value of the scale of 3.0, distributed between 3.62 and 3.86. This demonstrates that the banking professionals interviewed have generally positive attitudes towards AI-driven supply chain credit assessment and related aspects. The "Commercial Bank Credit Policy (CBCP)"has the highest mean, reaching 3.86 (standard deviation = 0.76), which implies that banks tend to adopt credit policies that are more conducive to SMEs, with the support of AI systems. The mean value of "Artificial Intelligence-Enhanced Banking Cognition (CBAEC)" as an intermediary variable was 3.79 (standard deviation = 0.81), indicating that bank practitioners have indeed felt the significant improvement of AI technology in their cognitive abilities. The mean values of the independent variables "Small and Medium Enterprise Credit Situation (SCS)" and "Core Enterprise Influence (CEI)" were 3.62 and 3.74, respectively, and the mean values of the moderating variable "Accuracy of Artificial Intelligence

Assessment (AAA)" were 3.68. These mean values reflect the general recognition of the importance of these factors under the AI evaluation framework.

Judging from the distribution pattern of the data, the absolute values of Skewness and Kurtosis of all variables are less than 1, which is far within the acceptable standard distribution judgment criteria (usually ±2). The skewness values are all negative, indicating that the data distribution is slightly tilted to the right, that is, most of the scores are concentrated in higher fractional segments. In contrast, the kurtosis values are all positive, indicating that the data distribution pattern is more concentrated than the standard normal distribution. These results jointly verify that the data meet the normality assumption required by subsequent parameter tests (such as structural equation model analysis), providing guarantees for the accuracy of the analysis.

Table 4.3 Descriptive statistics of core research variables (N = 360)

Variable (concept)	Mean	Standard deviation	Minimum value	Maximum value	Skewness	Kurosion
Credit Status of Small and Medium Enterprises (SCS)	3.62	0.78	1.00	5.00	-0.48	0.32
Core Enterprise Influence (CEI)	3.74	0.82	1.00	5.00	-0.56	0.41
Commercial Bank Credit Policy (CBCP)	3.86	0.76	1.00	5.00	-0.62	0.53
Banking Cognition Enhanced by Artificial Intelligence (CBAEC)	3.79	0.81	1.00	5.00	-0.58	0.47
Artificial Intelligence Assessment Accuracy (AAA)	3.68	0.84	1.00	5.00	-0.52	0.38

In order to initially explore the strength and direction of the relationship between each core variable and provide a priori basis for subsequent causal model testing, this study calculated the Pearson Correlation Coefficient between the five core variables. The analysis results are shown in Table 4.4.

The results showed a statistically significant ($p < 0.001$) positive correlation between all core variables, which provided preliminary and strong support for the hypothesis proposed in this study. Specifically, the two independent variables "Small and Medium Enterprise Credit Status (SCS)" and "Core Enterprise Influence (CEI)" and the dependent variable "Commercial Bank Credit Policy (CBCP)" show strong correlations, with correlation coefficients being 0.615 and 0.642, respectively, which preliminarily confirms the rationality of H1 and H2.

At the same time, there is also a strong correlation between the mediating variable "Artificial Intelligence-Enhanced Banking Cognition (CBAEC)" and the independent variable (r is 0.578 and 0.608, respectively) and the dependent variable (r=0.681). This general strong correlation suggests that CBAEC may play a vital bridge between independent and dependent variables, providing clues for subsequent testing of mediating effects hypothesis (H3, H4).

In addition, the moderating variable "AAA" also showed a moderate to strong positive correlation with all other variables (the correlation coefficient range is 0.523 to 0.589). This indicates that the higher the accuracy of the evaluation of the AI system, the higher the assessment of SME credit and core corporate influence by banking practitioners, their AI enhancement awareness is stronger, and ultimately they are more inclined to adopt favorable credit policies. This finding lays the foundation for testing the regulation effect hypothesis (H5). It is worth noting that although there are strong correlations between variables, all correlation coefficients are below the critical value of 0.80, indicating that the multicollinearity problem between variables is within an acceptable range and will not cause severe interference to subsequent structural equation model analysis.

Table 4.4 Core variable correlation coefficient matrix (N = 360)

Variable	1. SCS	2. CEI	3. CBCP	4. CBAEC	5. AAA
1. SCS	1				
2. CEI	.584**	1			
3. CBCP	.615**	.642**	1		
4. CBAEC	.578**	.608**	.681**	1	
5. AAA	.523**	.561**	.589**	.573**	1

Note: $p < 0.01$ (two-tailed test)

3.2 Measurement model verification

After conducting a preliminary descriptive analysis of the data, this study entered the critical step in structural equation model analysis - measurement model verification. In this stage, the reliability and validity of the measurement tools of this study were strictly evaluated through confirmatory factor analysis (CFA), to ensure that the measurement items in the questionnaire can accurately and stably reflect the theoretical concepts they want to measure.

This study used AMOS 24.0 software to construct a five-factor measurement model containing all five core concepts (SCS, CEI, CBCP, CBAEC, AAA) and their 25 observational topics. The overall fit evaluation results of the model show that the model has reached a very ideal fit level with the collected actual data.

The specific fit index is shown in Table 4.5. The chi-square value (Chi-square, χ^2) is 450.24, the degree of freedom (df) is 242, and the calculated chi-square degree of freedom ratio (χ^2/df) is 1.860. This value is significantly lower than the generally accepted 3.0 standard in academia and even below the stricter 2.0 standard, indicating good simplicity of the model. The excellent criterion with an approximate error root mean square (RMSEA) of 0.049, which is lower than 0.05, indicating that the residuals between the model and the data are minimal In addition, several key value-added fitting indexes also performed well: the comparative fitting index (CFI) was 0.954 and the Tucker-Lewis index (TLI) was 0.947, which were much higher than the recommended criterion of 0.90. Finally, the standardized residual root mean square (SRMR) is 0.041, also below the strict standard of 0.05. Overall, this series of ideal fitting indexes jointly prove that the five-factor measurement model constructed in this study can very well represent the sample data, and its structure is highly reasonable and valid, and can be used for subsequent reliability and validity analysis.

Table 4.5 Overall fit index of measurement model

Fit index	Symbol	Model value	Recommended criteria	Fitting evaluation
Chi-square degree of freedom ratio	χ^2/df	1.860	< 3.0	Excellent
Approximate error root mean square	RMSEA	0.049	< 0.08	Excellent
Comparison of fit index	CFI	0.954	> 0.90	Excellent
Tucker-Lewis Index	TLI	0.947	> 0.90	Excellent
Standardized residual root mean square	SRMR	0.041	< 0.08	Excellent

After confirming the overall fit of the model, this study further conducted a detailed test of the reliability and convergence validity of each construct, and the results are shown in Table 4.6.

In terms of reliability, this study uses two indicators: Cronbach's alpha (Cronbach's α) and Composite Reliability (CR) to measure internal consistency. The results show that the Cronbach's α values for all five constructs ranged from 0.853 to 0.894, and the CR values ranged from 0.856 to 0.896. All values of these two indicators are well above the accepted standard of 0.70, which shows that the measurement items of each construct in this study have very high intrinsic consistency and stability, and the measurement results of the questionnaire are highly reliable.

In terms of convergent validity, this study mainly evaluated through standardized factor loading and Average Variance Extracted (AVE). As seen from Table 4.6, the standardization factor loads of all 25 measurement questions ranged from 0.703 to 0.854, all above the ideal standard of 0.70, which shows that each question can reflect the latent variable it belongs to very effectively. More importantly, the AVE values for all five constructs ranged from 0.543 to 0.635, all exceeding the recommended threshold of 0.50. This shows that the amount of variation that each construct can explain through its measurement items exceeds the amount of variation that can be explained by the measurement error, proving that each construct has good convergence validity. Its measurement items are effectively converged on the same theoretical construct.

Table 4.6 Analysis results of reliability and convergence validity of measurement models

Concept	Questions	Normalized factor loading	Cronbach's α	CR	AVE
SME Credit Status (SCS)	SCS1	.786	.879	.881	.598
	SCS2	.812			
	SCS3	.798			
	SCS4	.756			
	SCS5	.731			
Core Enterprise Influence (CEI)	CEI1	.823	.853	.856	.543
	CEI2	.758			
	CEI3	.719			
	CEI4	.745			
	CEI5	.703			

Table 4.6 (Continued)

Concept	Questions	Normalized factor loading	Cronbach's α	CR	AVE
Commercial Bank Credit Policy (CBCP)	CBCP1	.841	.894	.896	.635
	CBCP2	.829			
	CBCP3	.807			
	CBCP4	.785			
	CBCP5	.749			
AI-enhanced Banking Cognition (CBAEC)	CBAEC1	.846	.887	.889	.617
	CBAEC2	.812			
	CBAEC3	.796			
	CBAEC4	.773			
	CBAEC5	.741			
AI Assessment Accuracy (AAA)	AAA1	.854	.876	.878	.590
	AAA2	.786			
	AAA3	.759			
	AAA4	.732			
	AAA5	.708			

Discriminant Validity tests whether there is sufficient difference between different theoretical concepts, i.e., to ensure that the measured five different concepts in this study are indeed five different concepts, rather than the same or highly overlapping concepts. This study used two mainstream methods for testing.

The first is the Fornell-Larcker criterion, which is implemented by comparing the correlation coefficient between the AVE square root value of the construct and the construct. As shown in Table 4.7, this study compares the AVE square root value of each construct (shown in bold on the diagonal) with the correlation values of this construct and other constructs (numeric values on the non-diagonal). The results clearly show that each value on the diagonal (range from 0.737 to 0.797) is greater than all other correlation values for the row and column it is located. This result meets the strict requirements of the Fornell-Larcker criterion and provides strong evidence for the validity of the distinction between concepts.

The second type is the Heterotrait-Monotrait Ratio (HTMT) test. HTMT is considered a more robust and rigorous inspection method than the Fornell-Larcker criterion. This study calculated the HTMLT values for all construct pairs and found that the maximum value was 0.72 (between CBAEC and CBCP), much lower than the conservative critical value of 0.85 recommended by the academic community. This further powerfully demonstrates that the five core constructs in this study are conceptually independent and have excellent distinctive validity. Especially for the two newly proposed concepts of "Artificial Intelligence-Augmented Banking Cognition (CBAEC)" and "Artificial Intelligence Assessment Accuracy (AAA)" in this study, their HTMT value is 0.72, and the confidence interval of their correlation [0.51, 0.68] does not include 1.0. It also shows a significant chi-square difference through constraint model comparison ($\Delta\chi^2$ = 87.6, Δdf = 1, $p<0.001$), which fully confirms that they represent two completely different phenomena: one is the cognitive improvement after human-computer interaction, and the other is the technical performance of the AI system itself.

To sum up, through a comprehensive evaluation of overall fit, reliability, convergence validity and discriminative validity, we can conclude that the measurement model of this study is of very high quality, providing a solid and reliable measurement basis for subsequent hypothesis testing of structural models.

Table 4.7 Test of distinguishing validity of constructs (Fornell-Larcker criterion)

Concept	1. SCS	2. CEI	3. CBCP	4. CBAEC	5. AAA
1. SCS	.773				
2. CEI	.584	.737			
3. CBCP	.615	.642	.797		
4. CBAEC	.578	.608	.681	.785	
5. AAA	.523	.561	.589	.573	.768

Note: The bold value on the diagonal is the square root of each construct AVE. The non-diagonal value is the correlation coefficient between the constructs.

3.3 Structural Model Analysis and Hypothesis Test (SEM)

This paper constructs a structural equation model (SEM), as shown in Figure 4.1.

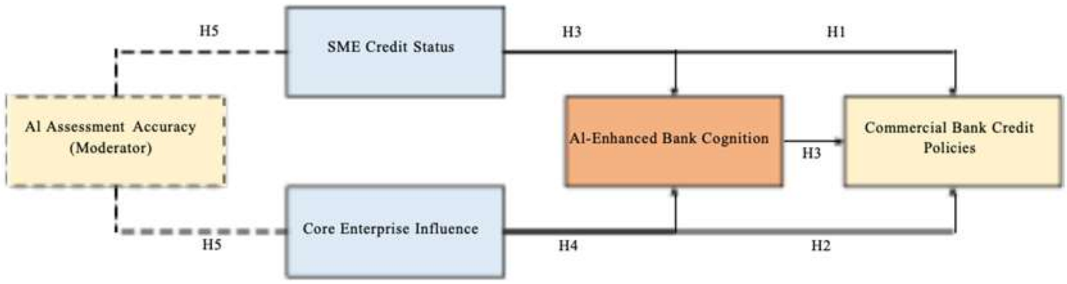

Figure 4.1 Structural Equation Model (SEM)

After successfully verifying the reliability and validity of the measurement model, this study entered the core hypothesis testing phase. This study systematically tests the five core hypotheses proposed in this study by constructing a structural equation model (SEM). First, this study evaluated the overall fit of the structural model, and the results showed that its fit index was ideal: $\chi^2/df=1.924$, RMSEA=0.051, CFI=0.951, TLI=0.944, SRMR=0.043. These indicators all meet the recommended criteria, indicating that the structural model can reflect the variable relationship in the data very well and is suitable for subsequent path analysis and hypothesis testing.

This study first examined the direct effects of the two independent variables on the dependent variable. The results of the specific paths are shown in Table 4.8.

Assuming H1 predicts that under the AI evaluation framework, the credit status of SMEs (SCS) has a significant positive impact on the credit policy of commercial banks (CBCP). The analysis results showed that the normalized path coefficient (β) pointed from SCS to CBCP was 0.285 and achieved extremely high statistical significance at the level of $p < 0.001$ (t value was 5.938). This result strongly supports H1, indicating that when banks use AI systems for evaluation, the better the credit status of SMEs themselves (such as stable operations and transparent finances), the more favorable the credit policies they obtain (such as higher approval rates and lower interest rates). This confirms that AI technology can effectively identify and positively feedback the high-quality credit of small and medium-sized enterprises.

Assuming H2 predicts that core enterprise influence (CEI) has a significant positive impact on commercial bank credit policy (CBCP). The test results also support this hypothesis. The normalized path coefficient (β) pointed from CEI to CBCP is 0.317, with a t value of up to 6.216, which is also highly significant at $p < 0.001$. This shows that in the supply chain finance scenario empowered by AI, the strong influence of core enterprises (such as industry reputation and payment reliability) can be effectively captured by the AI system and directly transformed into a more relaxed credit policy for related small and medium-sized enterprises. It is worth noting that the direct effect coefficient of core enterprise influence (0.317) is slightly higher than the coefficient of credit status of small and medium-sized enterprises (0.285), which to some extent implies that in the AI evaluation system, the overall relationship and network effects of the supply chain may play a more critical role than the credit of a single enterprise.

Table 4.8 Direct effect and regulatory effect path test results

Assumptions	path	Standardized path coefficient (β)	Standard error (S.E.)	t value	p value	Result
H1	SCS ⟶ CBCP	0.285	0.048	5.938	***	Support
H2	CEI ⟶ CBCP	0.317	0.051	6.216	***	Support
H5a	SCS × AAA ⟶ CBCP	0.124	0.029	4.276	***	Support
H5b	CEI × AAA ⟶ CBCP	0.138	0.031	4.452	***	Support

Note: *** $p < 0.001$

After verifying the direct effect, this study further examines the mediating role of "Artificial Intelligence-enhanced Banking Cognition (CBAEC)". This study used a deviation-corrected non-parametric percentile Bootstrapping method (5000 replicate samples) to estimate the indirect effect and its confidence interval, which is considered to be the most robust mediating effect testing method at present. The detailed results are shown in Table 4.9.

Hypothesis H3 proposes that CBAEC plays an intermediary role between the credit status of small and medium-sized enterprises (SMES) and the credit policy of commercial banks (CBCP). The analysis results show that the standardization coefficient of the indirect effect path (SCS ⟶ CBAEC ⟶ CBCP) through CBAEC is 0.167, and its 95% confidence interval is [0.112, 0.224]. Since the interval does not contain zero at all, it can be determined that the indirect effect is statistically significant. At the same time, after the introduction of mediating variables, the direct impact of SCS on CBCP (β=0.285) remained significant although it decreased numerically. This shows that CBAEC plays a part in the role of intermediary in it. In other words, the good credit of small and medium-sized enterprises can not only directly prompt banks to relax policies, but more importantly, it can indirectly affect credit policies by improving banks' awareness and judgment (with the assistance of AI). This indirect effect accounts for 37.0% of the total (0.452). Therefore, H3 has strong support.

Hypothesis H4 proposes that CBAEC also plays an intermediary role between core enterprise influence (CEI) and commercial bank credit policy (CBCP). The test results are similar to H3. The normalization coefficient of the indirect effect path (CEI ⟶ CBAEC ⟶ CBCP) through CBAEC was 0.193, with a 95% confidence interval of [0.134, 0.257], which also did not contain 0, indicating that the indirect effect was significant. The direct effect of CEI on CBCP (β=0.317) remains significant after introducing the mediating variable, confirming that CBAEC also plays a partial mediating role in it. The strong influence of core enterprises directly enhances banks' willingness to lend, and on the other hand, it also indirectly promotes better credit policies by strengthening banks' AI. This indirect effect accounts for 37.8% of the total (0.510). Therefore, H4 has also received strong support.

Table 4.9 Mediation effect test results (Bootstrapping, 5000 samples)

Intermediary path	Direct effect(c')	Indirect effect(a*b)	Total effect(c)	95%Confidence interval	Intermediary type
SCS ⟶ CBAEC ⟶ CBCP	0.285***	0.167***	0.452***	[0.112, 0.224]	Some intermediaries
CEI ⟶ CBAEC ⟶ CBCP	0.317***	0.193***	0.510***	[0.134, 0.257]	Some intermediaries

Note: *** $p < 0.001$

Finally, this study examines the moderating effect of "Accuracy of Artificial Intelligence Assessment (AAA)". This study tested the interaction terms by constructing and putting them into the structural model, and the results are also presented in Table 4.8.

Assuming H5a predicts, AAA can forwardly regulate the effect of SCS on CBCP. The test results show that the interaction term (SCS×AAA) obtained by multiplication of SCS and AAA centered by SCS has a path coefficient of 0.124 to CBCP and is highly significant at the level of $p < 0.001$ (t value is 4.276). This suggests that the accuracy of AI evaluation does play an important positive moderating role. In other words, with the improvement of the accuracy of AI systems, the positive impact of good credit status of small and medium-sized enterprises on obtaining preferential credit policies will strengthen. Therefore, H5a is supported.

Assuming H5b predicts, AAA can forwardly regulate the effect of CEI on CBCP. The test results are equally significant. The path coefficient of the interaction term (CEI × AAA) to CBCP is 0.138 ($p < 0.001$, t value is 4.452), confirming that AAA also plays an essential positive adjustment role in this path. This means that when the AI systems banks use are more accurate and reliable, the influence of core enterprises can be effectively transformed into actual credit support for small and medium-sized enterprises in the chain. Therefore, H5b is also supported.

To demonstrate this regulation effect more intuitively, a simple slope analysis was performed in this study. The results show that in groups with high accuracy in AI evaluation (one standard deviation above the mean), the path coefficients of SCS and CEI on CBCP (0.396 and 0.421, respectively) were significantly greater than those in groups with low accuracy (one standard deviation below the mean) (0.198 and 0.215, respectively). This result further verifies the existence and direction of the regulation effect, highlighting the core value of high-quality AI technology in unleashing the financial potential of supply chains.

3.4 Results of the analysis of observation points

(1) SME Credit Profile Analysis

Table 4.10 presents the descriptive statistics for the four observation points of SME's creditworthiness. The mean scores for each of the observation points are close to 3.15, indicating that respondents' evaluations of SME in these areas are relatively neutral. The standard deviations are around 0.2, indicating a low degree of dispersion in respondents' evaluations. The 'market reputation' score (3.18) is slightly higher than the other three observations (3.14), suggesting that market reputation may play a relatively important role in commercial banks' assessment of SMEs' creditworthiness.

Table 4.10 Descriptive statistics for each observation of SME credit status

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Financial situation	Item1-Item4	3.14	0.21	Financial situation
Compliance	Item5-Item8	3.14	0.20	Compliance
Market reputation	Item9-Item12	3.18	0.22	Market reputation
Supply Chain Status	Item13-Item16	3.14	0.20	Supply Chain Status

(2) CE Impact Analysis

Table 4.11 presents the descriptive statistics for the four observation points of CE influence. The mean scores for all four observation points are around 3.0, indicating that respondents are relatively neutral in evaluating CE's performance in these areas. The standard deviation is around 0.2, indicating a low degree of dispersion in respondents' evaluations. The score for 'Risk Management and Control Capability' (2.97) is slightly lower than the other three observation points, which may reflect the fact that respondents believe that there is still room for improvement in CE's risk management.

Table 4.11 Descriptive statistics for each observation of CE influence

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Risk management and control capabilities	Item17-Item20	2.97	0.22	Risk management and control capabilities
Networks and bargaining power	Item21-Item24	3.03	0.21	Networks and bargaining power
Market Reputation and Brand Influence	Item25-Item28	3.02	0.24	Market Reputation and Brand Influence
Information-sharing capacity	Item29-Item32	3.00	0.20	Information-sharing capacity

(3) BC Cognitive Analysis

Table 4.12 presents the descriptive statistics for the three observation points of BC perception. The mean scores for each observation point are all around 3, indicating that respondents are relatively neutral in their evaluation of BC's competence in these areas. The standard deviations are around 0.15, indicating a low degree of dispersion in respondents' evaluations. The score for 'credit risk identification' (3.03) is slightly lower than the other two observations (3.07 and 3.04), which may reflect respondents' perception that there is still room for improvement in commercial banks' credit risk identification.

Table 4.12 Descriptive Statistics for BC Cognition by Observations

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Credit risk identification capability	Item33-Item36	3.03	0.16	Credit risk identification capability
Financing needs assessment capacity	Item37-Item40	3.07	0.16	Financing needs assessment capacity
Supply Chain Credit Structure Understanding	Item41-Item44	3.04	0.16	Supply Chain Credit Structure Understanding

(4) BC Credit Policy Analysis

Table 4.13 presents the descriptive statistics for the three observation points of BC credit policy. The mean scores for each observation point are all around 3.1, indicating that respondents are relatively neutral in their evaluation of the current BC credit policy. The standard deviations are around 0.16, indicating that the degree of dispersion in respondents' evaluations is not high. The score for 'credit approval standards' (3.19) is slightly higher than the other two observation points (3.15 and 3.18), which may reflect respondents' perception that commercial banks' credit approval standards are relatively more stringent.

Table 4.13 Descriptive statistics for each observation of BC credit policy

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Credit approval criteria	Item45-Item48	3.19	0.16	Credit approval criteria
Loan amount and term	Item49-Item52	3.15	0.16	Loan amount and term
Rate and Fee Setting	Item53-Item56	3.18	0.17	Rate and Fee Setting

Chapter 5

Conclusion Discussion and Recommendations

This study, based on the theories of information asymmetry, relationship lending, group lending, and supply chain finance, constructs a comprehensive theoretical framework incorporating mediating and moderating effects to systematically explore the impact mechanism of AI-driven supply chain credit assessment on the credit policies of commercial banks towards small and medium-sized enterprises (SMEs). Through a questionnaire survey of 360 credit professionals from commercial banks in five representative cities in China and applying structural equation modeling (SEM) for empirical analysis, this study successfully verified all the preset hypotheses. It reached conclusions of significant theoretical value and practical significance.

Conclusions

The core conclusions of this study can be summarized into four points, which collectively depict a panoramic view of how AI technology is reshaping the credit assessment of small and medium-sized enterprises (SMEs).

1. The direct effects of the core assessment factors under AI empowerment are significant

The research results clearly show that under the AI assessment framework, two traditional key credit assessment factors - "SME credit status" (SCS) and "core enterprise influence" (CEI) - both have significant and positive direct impacts on "commercial bank credit policy" (CBCP). Specifically, the standardized path coefficient of SCS on CBCP is 0.285 ($p < 0.001$), and the path coefficient of CEI on CBCP is 0.317 ($p < 0.001$). This confirms hypotheses H1 and H2. This finding indicates that AI technology does not completely subvert the traditional credit review logic but, through its more powerful data processing capabilities, more accurately identifies and quantifies the credit value of SMEs themselves and their relationship value within the supply chain network, and directly transmits this to the policy-making level of banks.

2. "AI-enhanced bank cognition" is a key mediating bridge:

One of the most important findings of this study is that "Artificial Intelligence Enhanced Banking Cognition" (CBAEC) plays a crucial partial mediating role between SCS, CEI and CBCP. This supports H3 by confirming that AI-enhanced bank cognition mediates the relationship between SME credit status and bank credit policy. In practical terms, this means that AI tools not only process data but also shape how bankers interpret SME risk, thereby influencing policy decisions. This implies that the good creditworthiness of SMEs and the strong influence of CEIs not only affect the results directly as cold data inputs, but also through a process of "cognitive sublimation". That is, the AI system first helps credit officers to understand the data more deeply, perceive the risks more keenly, and make judgments more confidently. This cognitive ability enhanced by AI is the core internal mechanism that drives the adjustment of banks' credit policies in a better direction. The indirect effect accounts for 37.0% and 37.8% of the total impact, highlighting the huge role of this cognitive mediation path.

3. "AI Assessment Accuracy" as a Deterministic Moderator

This study further found that "AI Assessment Accuracy" (AAA) played a significant positive moderating role in the above relationship, and Hypothesis H5 was fully verified. The interaction term of SCS vs. AAA interaction term had an impact coefficient of 0.124 ($p < 0.001$) on CBCP, and the CEI interaction term with AAA had an impact coefficient of 0.138 ($p < 0.001$). This finding reveals a key practical truth: the application effect of AI technology does not happen overnight, and its quality - i.e., the accuracy of the algorithm, the reliability of the data, and the robustness of the system - directly determines the strength of its enabling effect. A high-precision AI system can become an “amplifier” for credit assessment, significantly enhancing the credit worthiness of high-quality SMEs and strong supply chains; on the contrary, a low-quality system may have little effect or even be misleading.

4. Supply chain network value is highlighted in AI assessment

Comprehensive comparison of the coefficients of each path reveals that, whether it is a direct effect (0.317 > 0.285) or an indirect effect (0.193 > 0.167), the influence of the core enterprise plays a slightly stronger role than that of the SME's credit status. To a certain extent, this shows that in the AI-driven assessment system, banks are increasingly emphasizing the overall assessment of SMEs in the supply chain ecosystem in which they are located. AI's powerful network analysis capability makes the "relationship value" and "network effect", which were difficult to quantify in the past, become visible and visible, and the "network effect" becomes visible. AI's powerful network analysis capabilities have made "relationship value" and "network effects", which were difficult to quantify in the past, visible and given higher weight.

Discussion

The findings of this study not only provide new empirical evidence for the application of AI in finance, but also constitute an essential supplement and deepening of existing theories and industry practices.

1. A new interpretation of traditional financial theories in the AI era

The results of this study are a powerful interpretation of how classic theories such as information asymmetry and relationship lending have evolved in the AI era. AI technology alleviates the information asymmetry problem between banks and SMEs by processing massive and multidimensional "alternative data" with unprecedented depth and breadth. This echoes Sadok et al. (2022). More importantly, this study reveals how AI can transform relationship lending theory from an "art" that relies on personal experience to a data-driven "science". -The AI system was able to quantify the impact of the core business - the quintessential "soft information" and "relationship capital" - and prove that it was worth even more than the SME's own "hard information". "hard information", which provides a concrete mechanistic explanation for Yin et al.'s (2020) study on the value of alternative data sources. This signifies an accelerated shift in the credit assessment paradigm from "collateral dependence" to "data and relationship dependence".

2. Revealing the "human-computer collaboration" of AI applications

By validating the mediating effect of "AI-enhanced bank cognition", this study reveals the true nature of the current stage of AI applications in complex decision-making - human-computer collaboration and cognitive enhancement. -AI does not simply replace humans, but rather serves as a powerful cognitive aid that frees humans from tedious data processing and allows them to focus on strategic judgment and the ultimate weighing of risks. This finding of "partial mediation" is highly consistent with the model of collaborative human-machine decision-making proposed by De Lange et al. (2022), which strongly refutes extreme views such as "AI omnipotence" or "AI threat theory". It strongly refutes extreme views such as "AI omnipotence" or "AI threat theory". The focus of future financial talent training is not on competing with AI for computing power, but on cultivating "two-brain" experts who can understand, master and collaborate with AI efficiently.

3. Emphasize the deep integration of technology quality and financial practice

The significant moderating effect of AI assessment accuracy is a wake-up call for the on-the-ground application of fintech. It suggests that the introduction of technology is only the first step; it is the quality of the technology and its fit with the business scenario that determines success or failure. This finding aligns with El Khair Ghoujdam (2024) comparative study that more advanced machine learning techniques lead to better risk analysis. When banks undergo digital transformation, they must avoid the technology cult of "AI for the sake of AI". They should strategically invest resources in building high-quality and highly reliable AI systems, and establish continuous model validation, iteration, and optimization mechanisms to ensure that the technology truly serves the core objectives of risk control and business development.

4. Extensions to the Theory of Information Asymmetry

This paper extends the theory of information asymmetry. Traditional theories posit that commercial banks' credit policies are influenced by the experiential judgements of credit officers. This study proposes that in the AI era, credit officers utilize AI technology, treating AI as a cognitive agent with information-processing capabilities. Their informational advantage no longer hinges on one party possessing greater data volumes, but rather on the overall quality and efficiency of information processing within the integrated system comprising commercial bank credit officers and AI. Consequently, the core variable of information asymmetry theory evolves from information possession to the quality and efficiency of cognitive updating, providing a new micro-theoretical foundation for explaining credit allocation within the digital finance environment.

Recommendations

1. Recommendations for Commercial Banks

This study provides a clear roadmap for commercial banks' digital transformation and credit business innovation. Banking institutions should prioritize strategic investments in high-quality AI systems, not only to purchase a set of software, but also to build core capabilities covering algorithm development, model validation and risk management. At the same time, banks need to reshape their traditional credit approval process and actively promote the evolution to the human-machine collaboration model of "AI initial review and expert review". To support this transformation, it is necessary to strengthen the training of existing credit staff in AI literacy and data analysis capabilities, so that they can be transformed from mere executives to decision makers who can understand and master AI tools [39]. In addition, banks should break down institutional barriers, deepen eco-cooperation with core supply chain enterprises, and securely and compliantly break through information silos by, for example, co-building data platforms, to maximize the analytical efficacy of AI models. Ultimately, based on AI's powerful dynamic risk insights, banks can and should go on to develop more data-driven innovative financial products, such as floating-rate loans based on supply chain health indexes or entirely online automatic approval order financing, to truly realize the unity of financial inclusion and business sustainability.

2. Suggestions for SMEs and Core Enterprises

For enterprises in the supply chain, this study is also of great guiding significance. SMEs should proactively embrace the wave of digitization and actively digitize key aspects of their finance, production, warehousing and sales. Improving the quality, completeness and transparency of their operating data is a key step to obtaining fair and favorable evaluations in the future AI credit assessment system. It is also a necessary way to improve their management efficiency. As for the core enterprises in the supply chain, they should fully recognize their "chain owner" responsibility and hub value in the data era. Core enterprises should use their central position to lead and promote the data standardization and collaborative sharing of the entire supply chain upstream and downstream. By opening the desensitized and authorized transaction data to financial institutions, core enterprises can not only provide substantial "data credit enhancement" for cooperative SMEs and effectively reduce their financing costs, but also build a more resilient, responsive and stable supply chain ecosystem, and ultimately achieve a win-win situation for all parties.

Future research

1. Limitations of the research design

While this study achieved insightful findings, its inherent design limitations must be confronted. First, the cross-sectional data design used in the study, while effective in revealing correlations between variables and complex pathways of influence, is limited in its ability to argue for strict causality, and this study is unable to completely rule out the possibility of reverse causation or the existence of common influences. Second, the source of data in this study relies on respondents' self-reporting. Although common methodological biases are tested by various statistical methods and considered not to be a serious problem in this study, individual subjective perception, memory bias, or social expectation effects may still have some impact on the absolute objectivity of the data. Finally, the representativeness of the sample has some limitations. Although it covers several cities and bank types, it mainly focuses on the more economically developed regions in China, and whether its conclusions can be generalized to the less economically developed areas or to completely different international financial systems without discrimination needs to be further verified.

2. Prospects for Future Research

Based on the findings and limitations of this study, future academic exploration may deepen in three directions. Firstly, employing longitudinal tracking or quasi-experimental designs, with policy shocks or technological rollouts as temporal markers, to systematically examine the long-term causal effects of AI credit assessment in developing economies characterized by divergent regulatory environments and weak data infrastructure. Second, conduct cross-national and cross-sector comparative studies, replicate the model across heterogeneous industries such as manufacturing and services to observe how differences in asset structures, cash flow characteristics, and supply chain finance requirements modulate the applicability boundaries of AI. Additionally, examine the moderating effects of varying data privacy regulations and financial cultures. Third, focus on cross-technology convergence effects to explore the complementary mechanisms and governance challenges that emerge when AI synergizes with blockchain, the Internet of Things, and privacy-preserving computation to construct a next-generation supply chain finance system that is trustworthy, intelligent, and privacy-friendly.

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Appendices

Appendix A

List of Specialists and Letters of Specialists Invitation

for IOC Verification

List of Specialists and Letters of Specialists Invitation for IOC Verification

Number	Name of Expert	Position/Office
1	Asst. Prof. Dr. Thun Chaitorn	Bansomdejchaopraya Rajabhat University
2	Prof. Wang XiaoLi	Guangxi University of Foreign Language, Head of Financial Engineering Programme
3	Prof. Li Danyun	Guangxi University of Foreign Languages, deputy chair of board

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for educational purposes for research studies student Doctor of Business Administration Program (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Wu Feng, Subject "Impact of Supply Chain Creditworthiness on Commercial Banks' Credit Policies for Small and Medium Enterprises". The questionnaire was made for Commercial bank credit practitioners in China. The researcher asks for help from experts. Please check the questionnaires as follows.

+1 means that you are sure that the questions are consistent with the research objective.

0 means you are unsure whether the question is consistent with the research objective.

-1 means that you are certain that the questions are inconsistent with the research objective.

With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) :Thun Chaitorn

Department:

Inspection date:2 October 2024

Location:

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for educational purposes for research studies student Doctor of Business Administration Program (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Wu Feng, Subject "Impact of Supply Chain Creditworthiness on Commercial Banks' Credit Policies for Small and Medium Enterprises". The questionnaire was made for Commercial bank credit practitioners in China. The researcher asks for help from experts. Please check the questionnaires as follows.

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-1 means that you are certain that the questions are inconsistent with the research objective.

With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) :Li Dan Yun
Department:Guangxi University of Foreign Languages
Inspection date:2 October 2024
Location:No. 19, Wuhe Avenue, Nanning, Guangxi, China

Seeking Clarification from Experts in Examining Research Instruments.

Dear experts,

This questionnaire for educational purposes for research studies student Doctor of Business Administration Program (International Program) in the Faculty of Management Science at Bansomdejchaopraya Rajabhat University prepared by Wu Feng, Subject "Impact of Supply Chain Creditworthiness on Commercial Banks' Credit Policies for Small and Medium Enterprises". The questionnaire was made for Commercial bank credit practitioners in China. The researcher asks for help from experts. Please check the questionnaires as follows.

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With the courtesy of your qualified, this makes this study a powerful research tool. This will be very useful for education. We would like to thank you very much for spending your valuable time reviewing the research instrument.

Expert (Name) :Wang Xiao Li

Department:Guangxi University of Foreign Languages

Inspection date:2 October 2024

Location:No. 19, Wuhe Avenue, Nanning, Guangxi, China

Appendix B

Official Letter

Ref.No. MHESI 0643.14/2735

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

2 October 2024

Subject: Invitation to validate research instrument

Dear Wang Xiao li

Mr.Wu Feng is a graduate student in Doctor of Business Administration Program (International Program) of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled "Impact of Supply Chain Creditworthiness on Commercial Bank's Credit Policies for Small and Medium Enterprises"

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Tanaput Chancharoen)
Vice Dean Acting for of Dean of Graduate School

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Ref.No. MHESI 0643.14/2736

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1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

2 October 2024

Subject: Invitation to validate research instrument

Dear Li Dan Yun

Mr.Wu Feng is a graduate student in Doctor of Business Administration Program (International Program) of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled "Impact of Supply Chain Creditworthiness on Commercial Bank's Credit Policies for Small and Medium Enterprises"

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Tanaput Chancharoen)
Vice Dean Acting for of Dean of Graduate School

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Thonburi Bangkok 10600

2 October 2024

Subject: Invitation to validate research instrument

Dear Assistant Professor Dr.Thun Chaitorn

Mr.Wu Feng is a graduate student in Doctor of Business Administration Program (International Program) of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled "Impact of Supply Chain Creditworthiness on Commercial Bank's Credit Policies for Small and Medium Enterprises"

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Tanaput Chancharoen)
Vice Dean Acting for of Dean of Graduate School

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Appendix C

Research Instrument

synopsis of an interview

Interviewees

Commercial Bank SME Credit Practitioners (10) - including Heads of Credit Departments and Employees Interviews

Part I: Enterprise creditworthiness

Financial health

1.Could you tell us about the impact of the financial health of SMEs on the credit decisions of commercial banks?

2.Which indicators do you consider most critical in assessing the financial health of SMEs? Why?

3.How do you think supply chain credit affects the financial health of SMEs?

4. How do you think commercial banks should better assess the financial health of supply chain SMEs?

Compliance capacity

5.Could you tell us about the impact of SMEs' ability to perform on commercial banks' credit decisions?

6. What aspects do you focus on when evaluating SMEs' ability to perform?

7.How do you think the evaluation of SMEs' performance capability by core supply chain enterprises affects commercial banks' credit decisions?

8. How do you think commercial banks should better assess the performance capability of supply chain SMEs?

Market reputation

9.Could you tell us about the impact of SMEs' market reputation on commercial banks' credit decisions?

10. How do you think commercial banks assess the market reputation of SMEs?

11. How do you think the market reputation of core supply chain firms affects SMEs' access to credit support?

12. How do you think commercial banks should better assess the market reputation of supply chain SMEs?

Supply chain position

13.Could you please comment on the impact of SMEs' position in the supply chain on their access to credit support?

14.What factors do you think determine the position of SMEs in the supply chain?

15.How do you think commercial banks should assess the position of SMEs in the supply chain?

16.What do you think SMEs should do to improve their position in the supply chain in order to obtain more credit support?

Part II: Core Corporate Influence

Risk management and control capacity

17.Could you tell us about the influence of the risk management and control capacity of core enterprises on the credit decisions of commercial banks?

18.In what ways do you think the risk management and control ability of core enterprises is reflected?

19.How do you think commercial banks should assess the risk management and control capability of core enterprises?

Networks and bargaining power

20.Could you tell us about the impact of core firms' networks and bargaining power on commercial banks' credit decisions?

21.How do you think core firms' networks and bargaining power affect SMEs' access to credit support?

22.How do you think commercial banks should assess the relationship network and bargaining power of core firms?

Market reputation and brand influence

23.Could you tell us about the impact of core firms' market reputation and brand influence on commercial banks' credit decisions?

24.How do you think the market reputation and brand influence of core enterprises affect the credit level and market position of SMEs?

25.How do you think commercial banks should assess the market reputation and brand influence of core enterprises?

Information-sharing capabilities

26.Could you tell us about the impact of core firms' information-sharing capabilities on commercial banks' credit decisions?

27.How do you think core enterprises should improve their information-sharing capabilities?

28.How do you think commercial banks should make use of the information-sharing capacity of core enterprises to better assess the credit risk of SMEs?

Part III: Perceptions of Commercial Banks

Credit Risk Identification Capabilities

29.Could you tell us what challenges commercial banks face in assessing SME credit risk?

30.How do you think commercial banks should improve their credit risk identification capabilities?

31.How do you think supply chain credit can help commercial banks identify SME credit risks?

Capacity to assess financing needs

32.Could you tell us how commercial banks assess the financing needs of SMEs?

33.What do you think commercial banks should do to improve their capacity to assess financing needs?

34.How do you think supply chain credit can help commercial banks assess SMEs' financing needs?

Supply chain credit structure understanding

35.Could you tell us about the extent of commercial banks' understanding of supply chain credit structures?

36.How do you think commercial banks should improve their understanding of supply chain credit structure?

37.How do you think an in-depth understanding of the supply chain credit structure can help commercial banks in their credit decisions?

Part IV: Commercial Bank Credit Policy

Credit approval criteria

38.Could you please talk about the impact of supply chain credit on commercial banks' credit approval standards?

39.How do you think commercial banks should adjust their credit approval criteria to better support supply chain SMEs?

Loan size and maturity

40.Could you please discuss the impact of supply chain credit on the setting of loan amount and maturity of commercial banks?

41.How do you think commercial banks should set the loan amount and term to better meet the financing needs of supply chain SMEs?

Interest rate and fee setting

42.Could you tell us about the impact of supply chain credit on commercial banks' interest rate and fee setting?

43.How do you think commercial banks should set interest rates and fees to better support the development of supply chain SMEs?

Guarantee and collateral requirements

44.Could you please discuss the impact of supply chain credit on commercial banks' guarantee and collateral requirements?

45.How do you think commercial banks should adjust their guarantee and collateral requirements to better support supply chain SMEs?

Questionnaire

Dear Sir/Madam

Hello! I am a doctor's student from the Bansomdejchaopraya Rajabhat University, Thailand. I am conducting a questionnaire survey on the study of factors influencing SME credit in commercial banks. This questionnaire was collected anonymously, and the personal information you provided is for academic research purposes only and will not be disclosed. Please fill out the survey truthfully based on your own situation. Thank you very much for your support. Sincerely thank you for your help and support in this survey questionnaire!

Part 1: Basic Information

1.Your bank type

❑ 1.Large state-owned commercial banks

❑ 2.Joint-stock commercial banks

❑ 3.city CITIC bank

❑ 4.private bank

❑ 5.foreign bank

❑ 6.Rural commercial banks

2.Your Position

❑ 1.Vice President, Credit Operations

❑ 2.Head of Credit Department

❑ 3. Credit department employees

❑ 4.other

3.Your years of experience

❑ 1.1-3 years

❑ 2.4-6 years

❑ 3.7-9 years

❑ 4.More than 10 years

4.Your City

❑1.Beijing

❑2.ShangHai

❑3.Guangzhou

❑4.Shenzhen

❑5.Nan Ning

Part II: Creditworthiness of SMEs (X variable of the paper)

Please click on the option (√) that applies to each of the questions listed below. Among them

1= Strongly disagree

2= Disagree

3= Neutral (neither agree nor disagree)

4= Agree

5= Strongly agree

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
1.Information in SMEs' financial statements is often not sufficiently complete and transparent.	❑	❑	❑	❑	❑
2.SMEs have volatile cash flows and are prone to financial chain breaks.	❑	❑	❑	❑	❑
3.SMEs are generally less profitable and less solvent.	❑	❑	❑	❑	❑
4.SMEs lack collateral and find it difficult to obtain bank loans.	❑	❑	❑	❑	❑
5.SMEs generally have low credit ratings and high credit risk.	❑	❑	❑	❑	❑
6.SMEs are weak in contract performance and prone to default.	❑	❑	❑	❑	❑
7.SMEs lack brand awareness and market presence.	❑	❑	❑	❑	❑
8.SMEs have a weak position in the supply chain and insufficient bargaining power.	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
9.The low level of information technology in SMEs makes it difficult to carry out effective credit management.	❑	❑	❑	❑	❑
10.It is difficult to assess the credit risk of small and medium-sized enterprises (SMEs), and the problem of information asymmetry is prominent.	❑	❑	❑	❑	❑
11.SMEs have a single source of financing and are overly dependent on bank loans.	❑	❑	❑	❑	❑
12.Higher credit default costs for SMEs result in higher losses for banks.	❑	❑	❑	❑	❑
13.There is room for improvement in the credit environment for SMEs, and there is a need to strengthen regulation and guidance.	❑	❑	❑	❑	❑
14.The credit system for small and medium-sized enterprises is lagging behind and lacks an effective credit assessment mechanism.	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
15.The credit information-sharing mechanism for small and medium-sized enterprises is imperfect, making it difficult to achieve information interoperability.	❑	❑	❑	❑	❑
16.SMEs are not sufficiently aware of credit risk and lack risk prevention measures.	❑	❑	❑	❑	❑

Part III: Core Enterprise Influence (X variable of the paper)

Please rate the following statements based on your knowledge of core business impact.

Rating scale:

1=Strongly disagree

2=Disagree

3=Neutral (neither agree nor disagree)

4=Agree

5=Strongly agree

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
17.Core firms have a dominant position in the supply chain and a strong influence on upstream and downstream firms.	❑	❑	❑	❑	❑
18.The core business has a strong financial position and low credit risk.	❑	❑	❑	❑	❑
19.The core enterprise has a good market reputation and brand influence.	❑	❑	❑	❑	❑
20.The core business has strong risk management and control capabilities.	❑	❑	❑	❑	❑
21.Core firms have a wide network of relationships and strong bargaining power.	❑	❑	❑	❑	❑
22.Core enterprises are able to provide financial support and guarantees to upstream and downstream enterprises in the supply chain.	❑	❑	❑	❑	❑
23.Core firms have a strong information-sharing capability and are able to transmit	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
supply chain information effectively.					
24.Core enterprises work closely with commercial banks and are able to provide effective credit guarantees.	❑	❑	❑	❑	❑
25.The stable development of core enterprises can contribute to the stable development of the entire supply chain.	❑	❑	❑	❑	❑
26.Core firms have an endorsement role in the creditworthiness of SMEs.	❑	❑	❑	❑	❑
27.Core firms can effectively reduce the cost of financing for SMEs.	❑	❑	❑	❑	❑
28.Core firms can facilitate the identification and management of credit risk in SMEs.	❑	❑	❑	❑	❑
29.Core businesses can help commercial banks better understand the business conditions of SMEs.	❑	❑	❑	❑	❑
30.Core enterprises can	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
promote the innovation and development of supply chain finance business.					
31.Core enterprises can effectively control supply chain finance risks.	❏	❏	❏	❏	❏
32.Core enterprises are the central force of the supply chain finance ecosystem.	❏	❏	❏	❏	❏

Part IV: Perceptions of Commercial Banks (Mediating Variables of the Paper)

Please rate the following statements based on your knowledge of commercial banking perceptions.

Rating scale:

1=Strongly disagree

2=Disagree

3=Neutral (neither agree nor disagree)

4=Agree

5=Strongly agree

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
33.Commercial banks are able to effectively identify SME credit risks.	❑	❑	❑	❑	❑
34.Commercial banks are able to accurately assess the financing needs of SMEs.	❑	❑	❑	❑	❑
35.Commercial banks have an in-depth understanding of supply chain credit structures.	❑	❑	❑	❑	❑
36.Commercial banks are able to effectively use supply chain credit information for credit decisions.	❑	❑	❑	❑	❑
37.Commercial banks are able to adjust their credit policies according to the creditworthiness of the supply chain.	❑	❑	❑	❑	❑
38.Commercial banks can effectively control supply chain finance risks.	❑	❑	❑	❑	❑
39.Commercial banks are actively engaged in supply chain finance business innovation.	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
40.Commercial banks have established good co-operative relationships with core businesses.	❑	❑	❑	❑	❑
41.Commercial banks are able to provide a full range of financial services to enterprises up and down the supply chain.	❑	❑	❑	❑	❑
42.Commercial banks attach importance to the construction of supply chain finance talent team.	❑	❑	❑	❑	❑
43.Commercial banks are actively exploring new models of risk management in supply chain finance.	❑	❑	❑	❑	❑
44.Commercial banks have taken supply chain finance as an important direction in their development strategy.	❑	❑	❑	❑	❑

Part V: Commercial Bank Credit Policies (Y variable of the paper)

Please rate the following statements based on your knowledge of commercial bank credit policies.

Rating scale:

1=Strongly disagree

2=Disagree

3=Neutral (neither agree nor disagree)

4=Agree

5=Strongly agree

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
45.Commercial banks have stricter credit approval criteria for SMEs.	❑	❑	❑	❑	❑
46.Commercial bank lending to SMEs is generally low.	❑	❑	❑	❑	❑
47.Commercial banks generally lend to SMEs for shorter periods.	❑	❑	❑	❑	❑
48. Interest rates on commercial bank loans to SMEs are generally high.	❑	❑	❑	❑	❑
49.Commercial banks require higher guarantees and	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
collateral from SMEs.					
50.Commercial banks lack flexibility in their credit policies towards SMEs.	❑	❑	❑	❑	❑
51. The efficiency of commercial banks' credit services to SMEs needs to be improved.	❑	❑	❑	❑	❑
52.Commercial banks' credit support for SMEs is inadequate.	❑	❑	❑	❑	❑
53.Commercial banks have weak credit risk management for SMEs.	❑	❑	❑	❑	❑
54.Commercial banks' credit policies towards SMEs are not consistent with national policy directions.	❑	❑	❑	❑	❑
55.Commercial banks' credit policies towards SMEs are not conducive to SME development.	❑	❑	❑	❑	❑
56.Commercial banks should increase their credit support	❑	❑	❑	❑	❑

state	Strongly disagree (1)	Disagree (2)	Neutral (neither agree nor disagree) (3)	Agree (4)	Strongly agree (5)
for small and medium-sized enterprises to promote their development.					

Questionnaire IOC Rating Scale

INSTRUCTIONS: Please specify the point of agreement between the question and the research objectives (Index of Project Objective Coherence (IOC)) in the gaps identified in the table below for each question. Please tick to select the choice that best matches the level of your opinion. If you have any further suggestions, please write them in the space provided.

Scoring Criteria:

+1 means that you can determine that the questions are consistent with the results of the study.

0 means that you are not sure that the questions are consistent with the results of the study.

-1 means that you are certain that the questions are not consistent with the results of the study.

Part II: Creditworthiness of SMEs (X-variable of the thesis)

Title Number	State	+1	0	-1	suggestion
1	Information in SMEs' financial statements is often not sufficiently complete and transparent.	❑	❑	❑	
2	SMEs have volatile cash flows and are prone to financial chain breaks.	❑	❑	❑	
3	SMEs are generally less profitable and less solvent.	❑	❑	❑	
4	SMEs lack collateral and find it difficult to obtain bank loans.	❑	❑	❑	
5	SMEs generally have low credit ratings and high credit risk.	❑	❑	❑	
6	Small and medium-sized enterprises (SMEs) have a weak capacity for contract performance and are prone to breach of contract.	❑	❑	❑	
7	SMEs lack brand awareness and market presence.	❑	❑	❑	
8	SMEs have a weak position in the supply chain and insufficient bargaining power.	❑	❑	❑	
9	Small and medium-sized enterprises (SMEs) have a low level of information technology, which makes it difficult for them to carry out effective credit management.	❑	❑	❑	
10	It is difficult to assess the credit risk of small and medium-sized enterprises (SMEs), and the problem of information	❑	❑	❑	

Title Number	State	+1	0	-1	suggestion
	asymmetry is prominent.				
11	SMEs have a single source of financing and are overly dependent on bank loans.	❑	❑	❑	
12	Higher credit default costs for SMEs result in higher losses for banks.	❑	❑	❑	
13	There is room for improvement in the credit environment for small and medium-sized enterprises (SMEs), and there is a need to strengthen regulation and guidance.	❑	❑	❑	
14	The credit system for SMEs is lagging behind and lacks an effective credit assessment mechanism.	❑	❑	❑	
15	The mechanism for sharing credit information on small and medium-sized enterprises (SMEs) is imperfect, making it difficult to achieve information interoperability.	❑	❑	❑	
16	Insufficient awareness of credit risk and lack of risk prevention measures among SMEs.	❑	❑	❑	

Part III: Core Enterprise Influence (X-variable of the paper)

Title Number	State	+1	0	-1	suggestion
17	Core enterprises have a dominant position in the supply chain and a strong influence on upstream and downstream enterprises.	❏	❏	❏	
18	The core business has a strong financial position and low credit risk.	❏	❏	❏	
19	Core companies have good market reputation and brand influence.	❏	❏	❏	
20	The core business has strong risk management and control capabilities.	❏	❏	❏	
21	The core companies have a wide network of relationships and strong bargaining power.	❏	❏	❏	
22	Core enterprises are able to provide financial support and guarantees to upstream and downstream enterprises in the supply chain.	❏	❏	❏	
23	Core firms have strong information sharing capabilities and are able to effectively transmit supply chain information.	❏	❏	❏	
24	Core enterprises work closely with commercial banks and are able to provide effective credit guarantees.	❏	❏	❏	

Title Number	State	+1	0	-1	suggestion
25	The stable development of core enterprises can promote the stable development of the whole supply chain.	❑	❑	❑	
26	Core firms have an endorsement role in the creditworthiness of SMEs.	❑	❑	❑	
27	Core firms can effectively reduce the cost of financing for SMEs.	❑	❑	❑	
28	Core firms can facilitate the identification and management of credit risk in SMEs.	❑	❑	❑	
29	Core businesses can help commercial banks better understand the business conditions of SMEs.	❑	❑	❑	
30	Core enterprises can promote the innovation and development of supply chain finance business.	❑	❑	❑	
31	Core enterprises can effectively control supply chain financial risks.	❑	❑	❑	
32	Core companies are the central force in the supply chain finance ecosystem.	❑	❑	❑	

Part IV: Perceptions of Commercial Banks (Mediating Variables for the Thesis)

Title Number	State	+1	0	-1	suggestion
33	Commercial banks are able to effectively identify SME credit risks.	❑	❑	❑	
34	Commercial banks are able to accurately assess the financing needs of SMEs.	❑	❑	❑	
35	Commercial banks have an in-depth understanding of supply chain credit structures.	❑	❑	❑	
36	Commercial banks are able to effectively use supply chain credit information to make credit decisions.	❑	❑	❑	
37	Commercial banks are able to adjust their credit policies according to the creditworthiness of the supply chain.	❑	❑	❑	
38	Commercial banks can effectively control supply chain finance risks.	❑	❑	❑	
39	Commercial banks are actively developing supply chain finance business innovation.	❑	❑	❑	
40	Commercial banks have established good relationships with core businesses.	❑	❑	❑	
41	Commercial banks are able to provide a full range of financial services to enterprises up and down the supply chain.	❑	❑	❑	

Title Number	State	+1	0	-1	suggestion
42	Commercial banks attach importance to the construction of supply chain finance talent team.	❑	❑	❑	
43	Commercial banks are actively exploring new modes of risk management in supply chain finance.	❑	❑	❑	
44	Commercial banks take supply chain finance as an important direction in their development strategy.	❑	❑	❑	

Part V: Commercial Bank Credit Policies (Y-variable of the paper)

Title Number	State	+1	0	-1	suggestion
45	Commercial banks have stricter credit approval criteria for SMEs.	❑	❑	❑	
46	Commercial bank lending to SMEs is generally low.	❑	❑	❑	
47	Commercial banks generally lend to SMEs for shorter periods.	❑	❑	❑	
48	Commercial banks generally charge higher interest rates on loans to SMEs.	❑	❑	❑	
49	Commercial banks require higher guarantees and collateral from SMEs.	❑	❑	❑	
50	Lack of flexibility in commercial banks' credit policies towards SMEs.	❑	❑	❑	
51	The efficiency of commercial banks' credit services to SMEs needs to be improved.	❑	❑	❑	
52	Insufficient credit support for SMEs from commercial banks.	❑	❑	❑	
53	Commercial banks have weak credit risk management for SMEs.	❑	❑	❑	
54	Commercial banks' credit policies towards SMEs are not consistent with national policy directions.	❑	❑	❑	
55	Commercial banks' credit policies towards SMEs are not conducive to SME development.	❑	❑	❑	
56	Commercial banks should increase their credit support for SMEs to promote their development.	❑	❑	❑	

Appendix D

The Results of the Quality Analysis of Research Instruments

Questionnaire IOC Rating Scale (Rating Data)

INSTRUCTIONS: Please specify the point of agreement between the question and the research objectives (Index of Project Objective Coherence (IOC)) in the gaps identified in the table below for each question. Please tick to select the choice that best matches the level of your opinion. If you have any further suggestions, please write them in the space provided.

Scoring Criteria:

□+1 means that you can determine that the questions are consistent with the results of the study.

□0 means that you are not sure that the questions are consistent with the results of the study.

□-1 means that you are certain that the questions are not consistent with the results of the study.

Part II: Creditworthiness of SMEs (X-variable of the thesis)

Title Number	State	+1	0	-1	suggestion
1	Information in SMEs' financial statements is often not sufficiently complete and transparent.				
2	SMEs have volatile cash flows and are prone to financial chain breaks.				
3	SMEs are generally less profitable and less solvent.				
4	SMEs lack collateral and find it difficult to obtain bank loans.				
5	SMEs generally have low credit ratings and high credit risk.				
6	Small and medium-sized enterprises (SMEs) have a weak capacity for contract performance and are prone to breach of contract.				
7	SMEs lack brand awareness and market presence.				
8	SMEs have a weak position in the supply chain and insufficient bargaining power.				
9	Small and medium-sized enterprises (SMEs) have a low level of information technology, which makes it difficult for them to carry out effective credit management.				
10	It is difficult to assess the credit risk of small and medium-sized enterprises (SMEs), and the problem of information				

Title Number	State	+1	0	-1	suggestion
	asymmetry is prominent.				
11	SMEs have a single source of financing and are overly dependent on bank loans.				
12	Higher credit default costs for SMEs result in higher losses for banks.				
13	There is room for improvement in the credit environment for small and medium-sized enterprises (SMEs), and there is a need to strengthen regulation and guidance.				
14	The credit system for SMEs is lagging behind and lacks an effective credit assessment mechanism.				
15	The mechanism for sharing credit information on small and medium-sized enterprises (SMEs) is imperfect, making it difficult to achieve information interoperability.				
16	Insufficient awareness of credit risk and lack of risk prevention measures among SMEs.				

Part III: Core Firm Influence (X-variable of the paper)

Title Number	State	+1	0	-1	suggestion
17	Core enterprises have a dominant position in the supply chain and a strong influence on upstream and downstream enterprises.				
18	The core business has a strong financial position and low credit risk.				
19	Core companies have good market reputation and brand influence.				
20	The core business has strong risk management and control capabilities.				
21	The core companies have a wide network of relationships and strong bargaining power.				
22	Core enterprises are able to provide financial support and guarantees to upstream and downstream enterprises in the supply chain.				
23	Core firms have strong information sharing capabilities and are able to effectively transmit supply chain information.				
24	Core enterprises work closely with commercial banks and are able to provide effective credit guarantees.				
25	The stable development of core enterprises can promote the stable development of the whole supply chain.				

Title Number	State	+1	0	-1	suggestion
26	Core firms have an endorsement role in the creditworthiness of SMEs.				
27	Core firms can effectively reduce the cost of financing for SMEs.				
28	Core firms can facilitate the identification and management of credit risk in SMEs.				
29	Core businesses can help commercial banks better understand the business conditions of SMEs.				
30	Core enterprises can promote the innovation and development of supply chain finance business.				
31	Core enterprises can effectively control supply chain financial risks.				
32	Core companies are the central force in the supply chain finance ecosystem.				

Part IV: Perceptions of Commercial Banks (Mediating Variables for the Thesis)

Title Number	State	+1	0	-1	suggestion
33	Commercial banks are able to effectively identify SME credit risks.				
34	Commercial banks are able to accurately assess the financing needs of SMEs.				
35	Commercial banks have an in-depth understanding of supply chain credit structures.				
36	Commercial banks are able to effectively use supply chain credit information to make credit decisions.				
37	Commercial banks are able to adjust their credit policies according to the creditworthiness of the supply chain.				
38	Commercial banks can effectively control supply chain finance risks.				
39	Commercial banks are actively developing supply chain finance business innovation.				
40	Commercial banks have established good relationships with core businesses.				
41	Commercial banks are able to provide a full range of financial services to enterprises up and down the supply chain.				
42	Commercial banks attach importance to the construction of supply chain finance talent team.				

43	Commercial banks are actively exploring new modes of risk management in supply chain finance.				
44	Commercial banks take supply chain finance as an important direction in their development strategy.				

Part V: Commercial Bank Credit Policies (Y-variable of the paper)

Title Number	State	+1	0	-1	suggestion
45	Commercial banks have stricter credit approval criteria for SMEs.	✓			
46	Commercial bank lending to SMEs is generally low.	✓			
47	Commercial banks generally lend to SMEs for shorter periods.	✓			
48	Commercial banks generally charge higher interest rates on loans to SMEs.	✓			
49	Commercial banks require higher guarantees and collateral from SMEs.	✓			
50	Lack of flexibility in commercial banks' credit policies towards SMEs.	✓			
51	The efficiency of commercial banks' credit services to SMEs needs to be improved.	✓			
52	Insufficient credit support for SMEs from commercial banks.	✓			
53	Commercial banks have weak credit risk management for SMEs.	✓			
54	Commercial banks' credit policies towards SMEs are not consistent with national policy directions.			✓	Suggested amendment: Commercial banks' credit policy towards SMEs is basically in line with the

Title Number	State	+1	0	-1	suggestion
					national policy orientation
55	Commercial banks' credit policies towards SMEs are not conducive to SME development.			✓	Proposed amendment to read: Commercial banks' credit policies towards SMEs are generally favourable to SME development
56	Commercial banks should increase their credit support for SMEs to promote their development.	✓			

Thesis Data Report

Table 3.1 List of Legal Persons in China's Banking Financial Institutions

Type of bank	Number of banks	Number of practitioners
Large state-owned commercial banks	6	——
Joint-stock commercial banks	12	——
city commercial bank	125	——
private bank	19	——
foreign bank	41	——
Rural commercial banks	1630	——
Total	**1833**	**Approximately 4 million**

Table 3.2 Sample Data on Commercial Bank Schemes by Type of Bank

Type of bank	Number of banks	Sample size (5 to 20 per cent)
Large state-owned commercial banks	6	1
Joint-stock commercial banks	12	2
City commercial bank	125	22
Private bank	19	3
Foreign bank	41	7
Rural commercial banks	1630	282
Total	**1833**	**317**

Table 3.3 Sampling plan by city

City name	Sample size
Nan Ning	120
Beijing	60
ShangHai	60
Guangzhou	60
Shenzhen	60
Total	**360**

Table 3.4 Expert Interviews

Master	Qualifications	Quorum
Commercial bank SME credit practitioners	Heads and employees of credit departments of commercial banks	30
Total		**30**

Table 3.5 Structure of the in-depth interviews

Variable	Number of Verses
Part 1 Small and Medium Enterprise Credit	
1.Financial health	3
2.Compliance	3
3.Market reputation	3
4.Supply Chain Status	3
Part 2 Core business influence	
1.Risk management and control capabilities	3
2.Relationship network and bargaining power	3
3.Market reputation and brand influence	3
4.Information-sharing capacity	3
Part 3 Commercial Banking Perceptions	
1. Credit risk identification capability	3
2. Financing needs assessment capacity	3
3.Supply Chain Credit Structure Understanding	3
Part 4 Commercial Bank credit policy	
1. Credit approval criteria	3
2.Loan amount and term	3
3.Rate and Fee Setting	3
Total	42

Table 3.6 Structure questionnaire

Variable	Number of verses	Clause	Data	Measurement
Part 1				
Small and Medium Enterprise Credit	16	12		
1.Financial health	(4)	1-4	Likert Scale	5 opinion levels
2.Compliance	(4)	5-8	Likert Scale	5 opinion levels
3.Market reputation	(4)	9-12	Likert Scale	5 opinion levels
4.Supply Chain Status	(4)	13-16	Likert Scale	5 opinion levels
Part 2				
Core business influence	16	16		
1.Risk management and control capabilities	(4)	17-20	Likert Scale	5 opinion levels
2.Relationship network and bargaining power	(4)	21-24	Likert Scale	5 opinion levels
3.Market reputation and brand influence	(4)	25-28	Likert Scale	5 opinion levels
4.Information-sharing capacity	(4)	29-32	Likert Scale	5 opinion levels
Part 3				
Commercial Banking Perceptions	12	12		
1. Credit risk identification capability	(4)	33-36	Likert Scale	5 opinion levels
2. Financing needs assessment capacity	(4)	37-40	Likert Scale	5 opinion levels
3.Supply Chain Credit Structure Understanding	(4)	41-44	Likert Scale	5 opinion levels
Part 4				
Commercial bank credit policy	12	12		

Variable	Number of verses	Clause	Data	Measurement
1.Credit approval criteria	(4)	45-48	Likert Scale	5 opinion levels
2.Loan amount and term	(4)	49-52	Likert Scale	5 opinion levels
3.Rate and Fee Setting	(4)	53-56	Likert Scale	5 opinion levels
Total	**56**			

Table 3.7 IOC content validity examiner (item objective congruence)

Experts	Experts Qualification	Number (person)
Statistical measurement and assessment experts in China	PhD, Professor in Statistics	1
Knowledge and Competence Scholars at Thai Universities	PhD Supervisor, Bansomdejchaopraya Rajabhat University	1
China's commercial banks' credit formulators	Designated Head of Credit Policy, People's Bank of China	1
Total		**3**

Table 3.8 Questionnaire structure and distribution of questions

Variables (Concepts)	Sub-dimension/measurement direction	number of questions
Creditworthiness of SMEs (SCS)	Business stability, repayment history, financial transparency, etc.	5
Core Corporate Influence (CEI)	Reputation, payment reliability, supply chain position, etc.	5
Artificial Intelligence Enhanced Banking Cognition (CBAEC)	Data Processing, Pattern Sensing, Decision Confidence, etc.	5
Artificial Intelligence Assessment Accuracy (AAA)	Algorithm accuracy, system reliability, error rate, etc.	5
Commercial Bank Credit Policy (CBCP)	Approval rate, amount, interest rate, efficiency, etc.	5

Table 3.9 Results of Pretest Reliability Analysis (Cronbach's α)

Variables (Concepts)	Number of questions	Cronbach's α	Reliability level
Creditworthiness of SMEs (SCS)	5	.885	Favourable
Core Corporate Influence (CEI)	5	.861	Favourable
Artificial Intelligence Enhanced Banking Cognition (CBAEC)	5	.892	Excellence
Artificial Intelligence Assessment Accuracy (AAA)	5	.879	Favourable
Commercial Bank Credit Policy (CBCP)	5	.903	Excellence
Overall questionnaire	25	.948	Excellence

Table 3.10 Statistics on Distribution and Return of Questionnaires

Items	Quantity (copies)	Proportions
Number of questionnaires planned for distribution	450	100%
Number of questionnaires actually returned	382	84.9%
Number of invalid questionnaires	22	4.9%
Final number of valid questionnaires	360	80.0%

Table 3.11 Some demographic variable coding schemes

Variable name	Category/Options	Coding
BankType	Large state-owned commercial banks	1
	Joint-stock Commercial Bank	2
	City Commercial Bank	3
	Rural Commercial Bank	4
	Private Bank	5
	Foreign-funded banks	6
Location	Beijing	1
	Shanghai	2
	Guangzhou	3
	Shenzhen	4
	Nanning	5

Table 3.12 Evaluation criteria for fitting of structural equation models

Fit index	symbol	Acceptable standards	References
Chi-square degree of freedom ratio	χ^2/df	< 3.0 (ideal< 2.0)	Kline (2016)
Approximate error root mean square	RMSEA	< 0.08 (ideal < 0.05)	Browne & Cudeck (1993)
Comparison of fit index	CFI	> 0.90	Bentler (1990)
Tucker-Lewis Index	TLI	> 0.90	Tucker & Lewis (1973)
Standardized residual root mean square	SRMR	< 0.08 (ideal < 0.05)	Hu & Bentler (1999)

Table 3.13 Criteria for agreeing on model conformity with empirical data.

Statistical values	Symbols	Acceptance Criteria	Reference
Chi-square	χ^2	-	
Degrees of freedom	Df	-	
Chi-square/ Degrees of freedom	χ^2/df	< 2	Wu Ming Long(2013)
probability	P-Value	>0.05	
Root means square error of approximation	RMSEA	<0.05	
Comparative Harmony Index (GFA)	CFI	>0.9	Jöreskog, K. G., & Sörbom, D. (1981)
Tucker-Lewis (AGFI)	TLI	>0.9	
Square root index of standard residuals.	SRMR	<0.05	

Table 4.1 Symbols and descriptions

Symbol	Explain
SME	Small and Medium-sized Enterprises
CE	Core Enterprise
BC	Commercial Bank
SCF	Supply Chain Finance
α	Cronbach's Alpha
KMO	Kaiser-Meyer-Olkin
CFA	Confirmatory Factor Analysis
EFA	Exploratory Factor Analysis
SEM	Structural Equation Modeling
χ^2	Chi-square
df	Degrees of Freedom
χ^2/df	Chi-square degree of freedom ratio
p	Level of significance (p-value)
RMSEA	Root Mean Square Error of Approximation
CFI	Comparative Fit Index
TLI	Tucker-Lewis
SRMR	Standardized Root Mean Square Residual
AVE	Average Variance Extracted
CR	Composite Reliability
β	Standardized path coefficients
CI	Confidence Interval
SME Credit	Credit status of small and medium-sized enterprises
CE Influence	Core corporate influence
BC Cognitio	Commercial Banking Cognition
BC Credit Policy	Commercial Bank Credit Policy
ACME	Average Causal Mediation Effect
ADE	Average Direct Effect
TE	Total Effect

Table 4.2 Sample demographic characteristics descriptive statistics (N=360)

Feature	Type	Frequency	Percentage
Bank Type	Private Bank	74	20.56%
	Large state-owned commercial banks	68	18.89%
	City Commercial Bank	63	17.50%
	Rural Commercial Bank	61	16.94%
	Foreign-funded banks	48	13.33%
	Joint-stock commercial bank	46	12.78%
Position	Deputy President in charge of credit business	100	27.78%
	other	95	26.39%
	Head of the credit department	87	24.17%
	Credit department staff	78	21.67%
Working years	1-3 years	104	28.89%
	4-6 years	92	25.56%
	7-9 years	86	23.89%
	More than 10 years	78	21.67%
City	Beijing	80	22.22%
	Guangzhou	77	21.39%
	Nanning	70	19.44%
	Shenzhen	67	18.61%
	Shanghai	66	18.33%

Table 4.3 Descriptive statistics of core research variables (N = 360)

Variable (concept)	Mean	Standard deviation	Minimum value	Maximum value	Skewness	Kurosion
Credit Status of Small and Medium Enterprises (SCS)	3.62	0.78	1.00	5.00	-0.48	0.32
Core Enterprise Influence (CEI)	3.74	0.82	1.00	5.00	-0.56	0.41
Commercial Bank Credit Policy (CBCP)	3.86	0.76	1.00	5.00	-0.62	0.53
Banking Cognition Enhanced by Artificial Intelligence (CBAEC)	3.79	0.81	1.00	5.00	-0.58	0.47
Artificial Intelligence Assessment Accuracy (AAA)	3.68	0.84	1.00	5.00	-0.52	0.38

Table 4.4 Core variable correlation coefficient matrix (N = 360)

Variable	1. SCS	2. CEI	3. CBCP	4. CBAEC	5. AAA
1. SCS	1				
2. CEI	.584**	1			
3. CBCP	.615**	.642**	1		
4. CBAEC	.578**	.608**	.681**	1	
5. AAA	.523**	.561**	.589**	.573**	1

Note: $p < 0.01$ (two-tailed test)

Table 4.5 Overall fit index of measurement model

Fit index	Symbol	Model value	Recommended criteria	Fitting evaluation
Chi-square degree of freedom ratio	χ^2/df	1.860	< 3.0	Excellent
Approximate error root mean square	RMSEA	0.049	< 0.08	Excellent
Comparison of fit index	CFI	0.954	> 0.90	Excellent
Tucker-Lewis Index	TLI	0.947	> 0.90	Excellent
Standardized residual root mean square	SRMR	0.041	< 0.08	Excellent

Table 4.6 Analysis results of reliability and convergence validity of measurement models

Concept	Questions	Normalized factor loading	Cronbach's α	CR	AVE
SME Credit Status (SCS)	SCS1	.786	.879	.881	.598
	SCS2	.812			
	SCS3	.798			
	SCS4	.756			
	SCS5	.731			
Core Enterprise Influence (CEI)	CEI1	.823	.853	.856	.543
	CEI2	.758			
	CEI3	.719			
	CEI4	.745			
	CEI5	.703			
Commercial Bank Credit Policy (CBCP)	CBCP1	.841	.894	.896	.635
	CBCP2	.829			
	CBCP3	.807			
	CBCP4	.785			
	CBCP5	.749			
AI-enhanced Banking Cognition (CBAEC)	CBAEC1	.846	.887	.889	.617
	CBAEC2	.812			
	CBAEC3	.796			
	CBAEC4	.773			
	CBAEC5	.741			
AI Assessment Accuracy (AAA)	AAA1	.854	.876	.878	.590
	AAA2	.786			
	AAA3	.759			
	AAA4	.732			
	AAA5	.708			

Table 4.7 Test of distinguishing validity of constructs (Fornell-Larcker criterion)

Concept	1. SCS	2. CEI	3. CBCP	4. CBAEC	5. AAA
1. SCS	.773				
2. CEI	.584	.737			
3. CBCP	.615	.642	.797		
4. CBAEC	.578	.608	.681	.785	
5. AAA	.523	.561	.589	.573	.768

Note: The bold value on the diagonal is the square root of each construct AVE. The non-diagonal value is the correlation coefficient between the constructs.

Table 4.8 Direct effect and regulatory effect path test results

Assumptions	path	Standardized path coefficient (**β**)	Standard error (S.E.)	t value	p value	Result
H1	SCS ⟶ CBCP	0.285	0.048	5.938	***	Support
H2	CEI ⟶ CBCP	0.317	0.051	6.216	***	Support
H5a	SCS × AAA ⟶ CBCP	0.124	0.029	4.276	***	Support
H5b	CEI × AAA ⟶ CBCP	0.138	0.031	4.452	***	Support

Note: *** $p < 0.001$

Table 4.9 Mediation effect test results (Bootstrapping, 5000 samples)

Intermediary path	Direct effect(c')	Indirect effect(a*b)	Total effect(c)	95%Confidence interval	Intermediary type
SCS ⟶ CBAEC ⟶ CBCP	0.285***	0.167***	0.452***	[0.112, 0.224]	Some intermediaries
CEI ⟶ CBAEC ⟶ CBCP	0.317***	0.193***	0.510***	[0.134, 0.257]	Some intermediaries

Note: *** $p < 0.001$

Table 4.10 Descriptive statistics for each observation of SME credit status

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Financial situation	Item1-Item4	3.14	0.21	Financial situation
Compliance	Item5-Item8	3.14	0.20	Compliance
Market reputation	Item9-Item12	3.18	0.22	Market reputation
Supply Chain Status	Item13-Item16	3.14	0.20	Supply Chain Status

Table 4.11 Descriptive statistics for each observation of CE influence

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Risk management and control capabilities	Item17-Item20	2.97	0.22	Risk management and control capabilities
Networks and bargaining power	Item21-Item24	3.03	0.21	Networks and bargaining power
Market Reputation and Brand Influence	Item25-Item28	3.02	0.24	Market Reputation and Brand Influence
Information-sharing capacity	Item29-Item32	3.00	0.20	Information-sharing capacity

Table 4.12 Descriptive Statistics for BC Cognition by Observations

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Credit risk identification capability	Item33-Item36	3.03	0.16	Credit risk identification capability
Financing needs assessment capacity	Item37-Item40	3.07	0.16	Financing needs assessment capacity
Supply Chain Credit Structure Understanding	Item41-Item44	3.04	0.16	Supply Chain Credit Structure Understanding

Table 4.13 Descriptive statistics for each observation of BC credit policy

Observation point	Constituent elements	Average score	standard deviation	Correspondence factor
Credit approval criteria	Item45-Item48	3.19	0.16	Credit approval criteria
Loan amount and term	Item49-Item52	3.15	0.16	Loan amount and term
Rate and Fee Setting	Item53-Item56	3.18	0.17	Rate and Fee Setting

Appendix E

Certificate of English

BANSOMDEJCHAOPRAYA
RAJABHAT UNIVERSITY

This is to certify that

Mr. Wu Feng

Achieved BSRU English Proficiency Test (BSRU-TEP) level

C1

Given on 22nd August 2021

(Assistant Professor Dr Kulsirin Aphiratvoradej)

Director

Appendix F

The Document for Acceptance Research

Future Publishing LLC

Advancing Knowledge Together

To

Mr. Nusanee Meekaewkunchom

Date: 05/24/2025

We are pleased to inform you that your paper, "Research on the Impact Mechanism of AI-Driven Supply Chain Creditworthiness Assessment on Commercial Banks' Credit Policies for SMEs" has been accepted for publication in the Future Technology Journal pending minor revisions.
Before we send the reviewer comments and issue the final acceptance, we kindly request that you complete the Article Processing Charge (APC) payment of $850 to the Future Publishing LLC account.
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Should you have any questions, feel free to reach out.

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Article

Research on the impact mechanism of AI-driven supply chain creditworthiness assessment on commercial banks' credit policies for SMEs

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ABSTRACT

This study investigates how AI-driven supply chain creditworthiness assessment transforms commercial banks' credit policies for small and medium-sized enterprises (SMEs), addressing the persistent SME financing gap through technological innovation. Using structural equation modeling, we analyzed data from 360 commercial banking professionals across China to test five hypotheses grounded in information asymmetry theory, relationship lending theory, group lending theory, and supply chain finance theory. SME credit status and core enterprise influence significantly impact bank credit policies (β = 0.285 and β = 0.317, $p < 0.001$), with AI-enhanced bank cognition serving as a partial mediator (indirect effects: β = 0.167 and β = 0.193, $p < 0.001$). Critically, AI assessment accuracy moderates these relationships, with higher-accuracy systems demonstrating stronger policy effects (β = 0.124 and β = 0.138, $p < 0.001$). AI fundamentally transforms SME credit evaluation by enhancing risk assessment accuracy, effectively leveraging supply chain relationships, and augmenting banks' cognitive capabilities. The moderating role of AI precision emphasizes the importance of technological sophistication for maximizing benefits. This research provides empirical evidence that AI-powered supply chain finance offers a viable solution to global SME financing constraints while maintaining robust risk management standards.

1. Introduction

Financing constraints faced by small and medium-sized enterprises (SMEs) pose a significant hindrance to the development of the global economy, particularly in light of complex supply network infrastructures. Larger players in supply chains currently hold considerable bargaining power, enabling them to procure raw materials from upstream suppliers [1]. The upstream supply chain primarily comprises SMEs that are incapable of acquiring services from commercial banks, mainly due to a lack of prior business history, a lack of transparency in the disclosure of information, and a lack of sufficient collateral [2]. The scenario increases the likelihood of default by large firms in making payments to upstream SMEs, thus raising serious doubts over the access of these small-scale enterprises to finance from financial institutions in the form of loans. These complexities create cash flow dilemmas within supply chains and create financial hazards along the supply channels [3]. Additionally, the limitations of conventional credit-based analyses have been demonstrated to be insufficient for managing the inherent complexities of such supply systems, underscoring the importance of incorporating AI-based evaluation methods in risk analysis and management [4]. Although AI technologies offer significantly advanced capabilities in assessing credit risks, there is a limited understanding of the impact of AI-enabled supply chain creditworthiness evaluation on commercial banks' lending policies for SMEs. How AI technology applies to the automation of traditional credit scoring systems and the context within which such systems operate most optimally remains largely unanswered. Consequently, this study intends to investigate the influence of AI-enabled supply chain creditworthiness assessment on commercial bank credit policies and SME lending. Specifically, the study identifies the mediating role of AI-enhanced bank cognition, investigates the moderating effect of AI assessment accuracy, and provides empirical evidence for the theoretical integration of AI technology with supply chain finance theories. In this regard, this study conducts an analysis of the technological upgrade of artificial intelligence on the traditional credit evaluation processes through the lens of information asymmetry theory, relationship lending theory, group lending theory, and supply chain finance theory.

Abbreviations	
AAA	AI Assessment Accuracy
AI	Artificial Intelligence
AVE	Average Variance Extracted
CBAEC	Commercial Bank AI-Enhanced Cognition
CBCP	Commercial Bank Credit Policies
CEI	Core Enterprise Influence
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
HTMT	Heterotrait-Monotrait
RMSEA	Root Mean Square Error of Approximation
SCS	SME Credit Status
SEM	Structural Equation Modeling
SME	Small and Medium-sized Enterprise
SRMR	Standardized Root Mean Square Residual
TLI	Tucker-Lewis Indexs

Additionally, this study analyses the collaboration of AI-enabled supply chain credit assessment and commercial bank credit policy in greater detail. The study demonstrates that AI technology can effectively improve the accuracy of commercial banks' assessment of SMEs' credit status, enhance the depth of their knowledge of the influence of core enterprises, and then optimise their credit policies. The impact mechanism operates through multiple pathways: AI enhances data processing capabilities, improves risk prediction accuracy, and enables real-time monitoring of supply chain dynamics. With the help of AI, commercial banks can better prevent supply chain credit risks and provide more accurate and efficient loan services for SMEs in the supply chain, thus resolving supply chain credit risks and helping the supply chain operate more smoothly and efficiently. This study provides a theoretical basis and practical reference for commercial banks to optimise supply chain credit policy using AI-driven assessment mechanisms, and promotes supply chain finance to achieve higher quality development under the empowerment of intelligent technology.

2. Literature review

2.1 Theoretical background

The information asymmetry theory, as first put forward by George Akerlof, basically examines the conditions under which market failures occur where parties to a transaction have disproportionate access to information. In the context of lending to SMEs, information asymmetry occurs in the sense that commercial banks lack full insights into the repayment capabilities of borrowers and the proposed uses of loans, leading to adverse selection and moral hazard issues. SMEs encounter significant obstacles in obtaining financing because of the information asymmetry problem, 'the gap', where banking firms do not have complete insight into understanding the financial health of the firm, negatively impacting both the efficiency and amount of loans granted [5]. AI technologies provide an effective remedy to such informational voids by scrutinising enormous volumes of unstructured data. Furthermore, banks are able to build sophisticated credit evaluation models that unearth a wealth of previously unrevealed relationships and interdependencies, thus realising their complete potential. The development of artificial intelligence in the financial services industry has moved beyond simple automation, advancing to include complex predictive analytics and real-time risk assessment capabilities. Machine learning-based techniques have the potential to identify meaningful patterns in various informational inputs, such as transactional data, social media activity, and communication within supply chains. In striving for this goal, such approaches seek to alleviate the information imbalances that have traditionally defined the relationship between lenders and small and medium-sized enterprise (SME) borrowers. These innovations allow commercial banks to look beyond traditional methods of credit analysis by incorporating alternative sources of information and altering risk assessment approaches in their analysis, enabling a more holistic evaluation of SME creditworthiness. The impact of such innovations is especially evident in the domain of supply chain finance, as artificial intelligence systems optimize the flow of information, capital, and operational efficiencies between firms involved in interdependent relationships. This shift gives rise to an unparalleled degree of transparency and promotes better-informed lending [6]. Government-backed initiatives, such as China's digital tax collection program, have shown that AI-driven solutions can successfully address information asymmetry and reduce risks stemming from stock price fluctuation by enhancing the quality of information disclosure [7]. During the period of the COVID-19 pandemic, the implementation of AI technologies across various business processes, such as targeting customers, cash flow control, as well as human resource control, has considerably reduced risks facing SMEs, hence underscoring the effectiveness of AI in countering information asymmetry in the light of unprecedented market volatility [8].

2.2 Relationship lending theory

Information asymmetry, as defined by Berger and Udell, is a relational lending theory based on a commercial bank's ability to mitigate information asymmetry over time with business partnerships. This theory revolves around four central aspects: gathering confidential or 'soft' information, controlling credit risk, improving credit management and decisions, including enhancing customer relations. Trust-oriented relationship banking goes a long way in easing the financing constraints of SMEs since understanding allows banks to perform more sophisticated credit evaluations. The introduction of artificial intelligence (AI) technologies has transformed the approaches employed in relationship lending by facilitating the automation of qualitative data collection and analysis, which previously posed daunting, quantifiable challenges. Advanced AI techniques can automatically process information from qualitative data, including emails, social media interactions, or even headlines, to digitally profile borrowers, capturing the essence of their relationship [9]. Improvements in AI technologies enable financial institutions to deploy relationship-driven analyses on a larger scope of SMEs while still offering the tailored analysis needed for relationship lending. Recent studies indicate that the merging of relationship lending with AI-driven analytics is vital to address the financing needs of SMEs and the post-pandemic information asymmetry deficit [10].

2.3 Group lending theory

The concept of group lending was developed by Bangladeshi economist Muhammad Yunus. This approach holds that financial institutions should group their clients into groups that get loans subsequently; in this context, all members of the group undertake joint responsibility for repayment of the loan. Each of the borrowers has the ability to repay the loan individually, but jointly accepts the responsibility with other group members with regard to the loans obtained by the group. The mutual discipline among participants serves as an economic incentive for loan repayment, as well as a common commitment to repayment. The existing body of evidence indicates that the nature of the loan relationship has a significant influence on the entrepreneurial and financial performance of small and medium-sized businesses, with a higher proportion of group lending programs being associated with greater access to finance [11]. The introduction of artificial intelligence (AI) technologies, particularly in performance evaluation, risk assessment, and network analysis, shifts the paradigm of practising group lending in supply chain transactions. Machine learning algorithms identify key clients and credit-risk distribution across interconnected firms while delineating increasingly complex business ecosystems [12]. Incorporating AI technology allows a financial institution to create adaptive group lending systems that respond to flexible frameworks of supply chains and turbulent market environments. AI-based platforms for supply chain finance can tremendously lower the information asymmetry cost in financial lending; small and medium-sized enterprises (SMEs) benefit from the endorsement and network effects of larger central enterprises [13].

2.4 Supply finance theory

The theory of supply chain finance elucidates those financial services that integrate information with logistics and the movement of capital within the supply chain networks. Due to the credit support from large firms, supply chain finance helps alleviate the funding gap of small and medium enterprises. It eases the payment burden of SMEs, especially those with favourable information sharing or located in financially well-developed regions [14]. This enables financial institutions to optimise working capital while minimising the financing costs incurred by all participants within the supply chain. The incorporation of artificial intelligence into the area of supply chain finance presents significant opportunities for conducting risk assessments, developing flexible pricing structures, and creating automated decision-making platforms. Artificial intelligence-driven algorithms have the potential to scan real-time information across the supply chain, hence enabling the forecasting of cash flow patterns, counterparty risk assessments, and the real-time adjustment of financing terms across volatile market conditions. Blockchain technology, in synergy with artificial intelligence for supply chain finance, is expected to greatly improve efficiency by streamlining information transfer and lowering verification costs [15]. Artificial intelligence-based supply chain finance platforms are expected to alleviate the financial strain on small and medium-sized businesses, as they enhance overall supply chain effectiveness through more intelligent information transfer and improved risk analysis techniques [16].

2.5 Hypothesis development

By applying theoretical models and the history of artificial intelligence usage in supply chain financing, the current study presents several hypotheses regarding the influence of artificial intelligence-based credit-scoring methods on the credit policies employed by commercial banks towards small and medium-sized enterprises (SMEs).

Hypothesis 1 (H1): The credit standing of an SME positively affects the commercial bank' s credit policies as a result of AI assessment. AI evaluation considers all components of an SME' s creditworthiness, thus qualifying SMEs receive better credit terms.

Hypothesis 2 (H2): The positive impact of core enterprises influence on commercial banks' credit policies is mediated by AI-powered evaluation. AI technology allows thorough examination of the core enterprise' s influence on the stability of the supply chain.

Hypothesis 3 (H3): Commercial bank AI-enabled cognition mediates the relationship between SME credit status and credit policies. Banks' understanding of financing requirements and credit risks is enhanced by AI systems.

Hypothesis 4 (H4): Commercial bank AI-enhanced cognition mediates the relationship between core enterprise influence and credit policies.

Hypothesis 5 (H5): AI assessment accuracy moderates the impact strength of the relationships between creditworthiness factors and credit policies.

The research framework depicted in Figure 1 illustrates the impact mechanism through which AI-driven creditworthiness assessment influences commercial banks' SME credit policies. The model demonstrates how traditional credit evaluation factors (SME credit status and core enterprise influence) are enhanced through AI technology, creating pathways to policy formulation. The mediating role of AI-enhanced bank cognition represents the cognitive augmentation process where AI systems help banks better understand and interpret credit-relevant information.

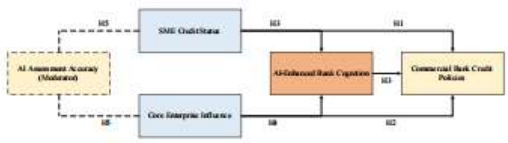

Figure 1. Research Framework

3. Research Methodology

3.1 Research Design and Data Collection

This study employs a quantitative research approach to investigate the impact mechanism of AI-driven supply chain creditworthiness assessment on commercial banks' credit policies for SMEs. A cross-sectional survey design was utilized to collect primary data from commercial banking professionals involved in credit assessment and policy formulation. The overall research design and data collection process are illustrated in Figure 2, which shows the systematic approach from theoretical framework development to empirical validation. The research follows a deductive approach, testing the proposed hypotheses derived from the theoretical framework that integrates information asymmetry theory, relationship lending theory, group lending theory, and supply chain finance theory. The target population comprises credit professionals from commercial banks across China. A purposive sampling technique was employed to ensure representation from different types of banking institutions and geographical regions. Five cities were strategically selected to provide comprehensive coverage: Beijing and Shanghai, as national financial centers representing advanced AI adoption; Guangzhou and Shenzhen, as regional financial hubs reflecting developed market dynamics; and Nanning, representing southwestern regional variations. Six bank types were included to capture sectoral diversity: large state-owned commercial banks, joint-stock commercial banks, urban commercial banks, rural commercial banks, private banks, and foreign banks, ensuring representation across different organizational scales, ownership structures, and business models that constitute China's banking landscape. The questionnaire was distributed electronically to credit personnel, including credit operations vice presidents and credit department directors, through professional networks and credit industry associations. Data collection was done from March to June 2024, after a pilot study of 30 bank professionals to test the questionnaire's validity and understandability before it was applied to the main survey. The questionnaire was posted to 450 bank professionals, and we received 360 usable returns, which represents an 80% response rate. The overall sample covers a wide range of views on AI-based credit assessment systems in the banking industry across institutions and geographical settings.

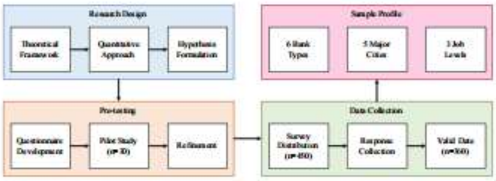

Figure 2. Research design and data collection process

3.2 Measurement instruments

3.2.1 Construct conceptualization and distinction

Commercial Bank AI-Augmented Cognition refers to the sophisticated cognition that bank professionals develop through their experience with AI systems in evaluating the credit risk of small and medium-sized enterprises. The phrase captures the interactive nature of human-AI collaborations and involves five major dimensions. The intensified data processing ability reflects the enhanced skill of bankers in handling complex, multidimensional data with the support of AI. The increased ability to recognize nuanced indicators of credit risk that are otherwise missed by standard analytic techniques is reflected in improved pattern perception. Their ability to make instantaneous evaluations of dynamic conditions with AI support is reflected in real-time evaluation capacity. Extended generation of insights represents an increased ability to integrate multiple sources of information to make meaningful evaluations. The elevated confidence in decisions reflects increased confidence in credit ratings with the aid of AI. Artificial intelligence evaluation precision measures the reliability and efficacy of AI systems independent of human intervention. The assessment focuses on technological and algorithmic aspects, including five unique dimensions. Algorithmic predictive correctness refers to the statistical soundness of credit risk evaluations generated by the AI system. Data quality refers to the comprehensiveness and reliability of input data used by the system. Model validation performance refers to the robustness of AI models under varying conditions and scenarios. System reliability refers to the consistency and accuracy of AI results over an extended period. Minimization of error rates is concerned with the system's ability to reduce false positives and false negatives in credit analysis.

The theoretical separation between these constructs is grounded in human-computer interaction literature, which distinguishes between system performance (technical capabilities) and user experience (cognitive enhancement). During survey development, several validation approaches confirmed this distinction: an expert panel review confirmed conceptual clarity, a pilot study's factor analysis revealed distinct factors with minimal cross-loadings, and item development employed different referents to ensure construct separation.

3.2.2 Scale Development and Measurement

The questionnaire was developed based on established scales from previous literature, adapted to the specific context of AI-driven creditworthiness assessment. All constructs were measured using 5-point Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). SME Credit Status was measured through items assessing business operational stability, repayment history, financial statement transparency, cash flow predictability, collateral adequacy, and overall credit risk profile. Core Enterprise Influence captured the impact of core enterprises on SME creditworthiness within supply chains through items measuring core enterprise reputation, payment reliability, supply chain position strength, and certification effects. Commercial Bank Credit Policies were operationalized through items addressing loan approval rates, credit limit flexibility, interest rate favorability, collateral requirements, loan processing efficiency, and overall policy supportiveness toward SMEs. Commercial Bank AI-Enhanced Cognition was measured through items assessing respondents' perceived enhancement in their cognitive abilities when using AI systems for credit evaluation. Sample items include: "AI systems have enhanced my ability to process complex SME financial data," "I can identify credit risk patterns more effectively with AI assistance," and "AI tools have improved my confidence in credit decision-making".

AI Assessment Accuracy was measured through items evaluating the technical performance and reliability of AI systems used in the respondents' banks. Sample items include: "The AI system in our bank provides accurate credit risk predictions," "The AI system consistently produces reliable assessment results," and "The AI system minimizes errors in credit evaluation". Control variables included bank type, bank size, respondent experience, geographic location, and the maturity of the AI system. To ensure the reliability and validity of the measurement, the questionnaire underwent rigorous pre-testing and refinement. The reliability of each construct was assessed using Cronbach's alpha coefficient, with values exceeding 0.7 considered acceptable for internal consistency. Additionally, item-total correlations were examined to identify items that might compromise scale reliability. Content validity was established through expert review by three senior banking professionals and two academic researchers specializing in financial technology. Construct validity was evaluated using exploratory factor analysis during the pilot study to ensure items loaded appropriately on their intended constructs.

3.3 Data analysis

Data analysis was performed using SPSS 26.0 and AMOS 24.0. Preliminary analyses included descriptive statistics and reliability testing using Cronbach's alpha (threshold of 0.7). Validity was assessed through composite reliability (CR), average variance extracted (AVE), the Fornell-Larcker criterion, and the heterotrait-monotrait (HTMT) ratio of correlations to further confirm discriminant validity. Common method bias was examined using Harman's single-factor test. The main analysis employed structural equation modeling (SEM), with confirmatory factor analysis (CFA) validating the measurement model before testing the structural model. Model fit was evaluated using multiple indices (χ^2/df, RMSEA, CFI, TLI, SRMR). Mediation effects were tested via bootstrapping with 5,000 samples to determine effect sizes and confidence intervals, distinguishing between full and partial mediation. Moderation effects were examined through interaction terms and multi-group analysis.

4. Results

4.1 Descriptive statistics and sample characteristics

The final sample consisted of 360 valid responses from commercial banking professionals across China, representing a diverse cross-section of the banking industry. Table 1 presents the demographic distribution of respondents and institutional characteristics. The sample demonstrated balanced representation across six major bank types, with private banks comprising the largest group (20.56%), followed by large state-owned commercial banks (18.89%), urban commercial banks (17.50%), rural commercial banks (16.94%), foreign banks (13.33%), and joint-stock commercial banks (12.78%). Geographic distribution covered five major Chinese financial centers: Beijing (22.22%), Guangzhou (21.39%), Nanning (19.44%), Shenzhen (18.61%), and Shanghai (18.33%), ensuring comprehensive regional coverage. Respondent experience levels were well-distributed, with 28.89% having 1-3 years of experience, 25.56% with 4-6 years, 23.89% with 7-9 years, and 21.67% with over 10 years in credit-related positions.

Table 1. Sample characteristics (N = 360)

Characteristic	Category	Frequency	Percentage
Bank Type	Private Banks	74	20.56%
	Large State-owned Banks	68	18.89%
	Urban Commercial Banks	63	17.50%
	Rural Commercial Banks	61	16.94%
	Foreign Banks	48	13.33%
	Joint-stock Banks	46	12.78%
Geographic Location	Beijing	80	22.22%
	Guangzhou	77	21.39%
	Nanning	70	19.44%
	Shenzhen	67	18.61%
	Shanghai	66	18.33%
Experience	1-3 years	104	28.89%
	4-6 years	92	25.56%
	7-9 years	86	23.89%
	10+ years	78	21.67%

Descriptive statistics for the main variables are presented in Table 2. All variables demonstrated satisfactory mean values above the midpoint of the 5-point scale, indicating positive perceptions of AI-driven creditworthiness assessment systems. SME Credit Status showed a mean of 3.62 (SD = 0.78), while Core Enterprise Influence scored slightly higher at 3.74 (SD = 0.82). Commercial Bank Credit Policies exhibited the highest mean value of 3.86 (SD = 0.76), suggesting banks' favorable stance toward SME lending when supported by AI assessment. The mediating variable, Commercial Bank AI-Enhanced Cognition, recorded a mean of 3.79 (SD = 0.81), and the moderating variable, AI Assessment Accuracy, showed a mean of 3.68 (SD = 0.84). Skewness and kurtosis values for all variables fell within the acceptable range of ±2, confirming normal distribution assumptions for subsequent analyses.

Table 2. Descriptive statistics of main variables

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
SME Credit Status	3.62	0.78	1.00	5.00	-0.48	0.32
Core Enterprise Influence	3.74	0.82	1.00	5.00	-0.56	0.41
Commercial Bank Credit Policies	3.86	0.76	1.00	5.00	-0.62	0.53
Commercial Bank AI-Enhanced Cognition	3.79	0.81	1.00	5.00	-0.58	0.47
AI Assessment Accuracy	3.68	0.84	1.00	5.00	-0.52	0.38

The correlation matrix revealed significant positive relationships among all main variables, providing preliminary support for the hypothesized relationships. SME Credit Status showed strong correlations with Commercial Bank Credit Policies ($r = 0.62$, $p < 0.001$) and Commercial Bank AI-Enhanced Cognition ($r = 0.58$, $p < 0.001$). Core Enterprise Influence demonstrated similarly strong associations with the dependent variable ($r = 0.64$, $p < 0.001$) and the mediating variable ($r = 0.61$, $p < 0.001$). The moderating variable, AI Assessment Accuracy, showed moderate to strong correlations with all other variables (ranging from $r = 0.52$ to $r = 0.59$, all $p < 0.001$), suggesting its potential role in strengthening the proposed relationships. These correlations, although indicating concerns about multicollinearity, remained below the critical threshold of 0.80, allowing for multivariate analysis.

4.2 Measurement Model Validation

The measurement model was assessed through confirmatory factor analysis (CFA) to establish the reliability and validity of the constructs. Table 3 presents the reliability and convergent validity results. All constructs demonstrated excellent internal consistency, with Cronbach's alpha values ranging from 0.853 to 0.894, well above the recommended threshold of 0.7. Composite reliability (CR) values similarly exceeded the 0.7 benchmark, ranging from 0.856 to 0.896, further confirming construct reliability. Average variance extracted (AVE) values for all constructs surpassed the 0.5 threshold, ranging from 0.543 to 0.635, indicating adequate convergent validity. Factor loadings for all items exceeded 0.7, with the majority above 0.8, demonstrating strong relationships between indicators and their respective constructs.

Discriminant validity was assessed using the Fornell-Larcker criterion, as shown in Table 4. The square root of each construct's AVE (shown on the diagonal) exceeded its correlations with other constructs, confirming discriminant validity. Additionally, the heterotrait-monotrait (HTMT) ratio of correlations was calculated, with all values below the conservative threshold of 0.85, providing further evidence of discriminant validity. The measurement model fit indices indicated excellent model fit: $\chi^2/df = 1.876$ (below the threshold of 3.0), RMSEA = 0.049 (below 0.08), CFI = 0.954 (above 0.90), TLI = 0.947 (above 0.90), and SRMR = 0.041 (below 0.08). These results confirmed that the measurement model adequately represented the data. Additional discriminant validity evidence was provided for AI-Enhanced Cognition and AI Assessment Accuracy constructs.

Table 3. Reliability and convergent validity

Construct	Items	Factor Loading	Cronbach's α	CR	AVE
	SCS1	0.786	0.879	0.881	0.598
	SCS2	0.812			
SME Credit Status	SCS3	0.798			
	SCS4	0.756			
	SCS5	0.731			
	CEI1	0.823	0.853	0.856	0.543
	CEI2	0.758			
Core Enterprise Influence	CEI3	0.719			
	CEI4	0.745			
	CEI5	0.703			
	CBCP1	0.841	0.894	0.896	0.635
	CBCP2	0.829			
Commercial Bank Credit Policies	CBCP3	0.807			
	CBCP4	0.785			
	CBCP5	0.749			
	CBAEC1	0.846	0.887	0.889	0.617
	CBAEC2	0.812			
Commercial Bank AI-Enhanced Cognition	CBAEC3	0.796			
	CBAEC4	0.773			
	CBAEC5	0.741			
	AAA1	0.854	0.876	0.878	0.590
	AAA2	0.786			
AI Assessment Accuracy	AAA3	0.759			
	AAA4	0.732			
	AAA5	0.708			

Table 4. Discriminant validity (Fornell-Larcker criterion)

Construct	1	2	3	4	5
1. SME Credit Status	0.773				
2. Core Enterprise Influence	0.584	0.737			
3. Commercial Bank Credit Policies	0.615	0.642	0.797		
4. Commercial Bank AI-Enhanced Cognition	0.578	0.608	0.681	0.785	
5. AI Assessment Accuracy	0.523	0.561	0.589	0.573	0.768

Note: Bold diagonal values are square roots of AVE.

The HTMT ratio between these two constructs was 0.72, well below the conservative threshold of 0.85. Moreover, the confidence interval of the correlation between these constructs [0.51, 0.68] did not include 1.0, providing strong evidence of discriminant validity. A constrained model where these two constructs were forced to correlate perfectly showed significantly worse fit ($\Delta\chi^2 = 87.6$, $\Delta df = 1$, $p < 0.001$) compared to the unconstrained model, confirming they represent distinct phenomena. Common method bias was assessed using Harman's single-factor test, which revealed that the first factor accounted for 38.7% of the variance, below the 50% threshold, suggesting that common method bias was not a significant concern. Additionally, a common latent factor approach was employed, where the standardized regression weights with and without the common latent factor showed minimal differences (less than 0.2), further confirming the absence of substantial method bias.

4.3 Hypothesis Testing

The structural equation model was employed to test the proposed hypotheses, with results presented in Table 5. The structural model demonstrated excellent fit indices: $\chi^2/df = 1.924$, RMSEA = 0.051, CFI = 0.951, TLI = 0.944, and SRMR = 0.043, indicating the model's appropriateness for hypothesis testing. Direct effects analysis revealed strong support for the primary relationships. Hypothesis 1, proposing that SME credit status positively influences commercial bank credit policies, was supported ($\beta = 0.285$, $p < 0.001$), confirming that banks with AI-enhanced evaluation systems respond favorably to SMEs with strong credit profiles. Hypothesis 2, suggesting that core enterprise influence positively affects commercial bank credit policies, was also supported ($\beta = 0.317$, $p < 0.001$), demonstrating the importance of supply chain relationships in AI-driven credit decisions.

Table 5. Results of hypothesis testing

Hypothesis	Path	Estimate	S.E.	t-value	p-value	Result
H1	SME Credit Status → Commercial Bank Credit Policies	0.285	0.048	5.938	***	Supported
H2	Core Enterprise Influence → Commercial Bank Credit Policies	0.317	0.051	6.216	***	Supported
H3	SME Credit Status → Commercial Bank AI-Enhanced Cognition → Commercial Bank Credit Policies	0.167	0.032	5.219	***	Supported
H4	Core Enterprise Influence → Commercial Bank AI-Enhanced Cognition → Commercial Bank Credit Policies	0.193	0.036	5.361	***	Supported
H5a	SME Credit Status × AI Assessment Accuracy → Commercial Bank Credit Policies	0.124	0.029	4.276	***	Supported
H5b	Core Enterprise Influence × AI Assessment Accuracy → Commercial Bank Credit Policies	0.138	0.031	4.452	***	Supported

Note: *** $p < 0.001$; S.E. = Standard Error

Mediation analysis using bootstrapping with 5,000 samples confirmed the mediating role of commercial bank AI-enhanced cognition. Hypothesis 3, proposing mediation between SME credit status and credit policies, was supported with a significant indirect effect ($\beta = 0.167$, 95% CI [0.112, 0.224]). The direct effect remained significant after including the mediator, indicating partial mediation. Similarly, Hypothesis 4, examining mediation between core enterprise influence and credit policies, was supported ($\beta = 0.193$, 95% CI [0.134, 0.257]), also demonstrating partial mediation. These findings suggest that AI-enhanced cognition serves as a critical mechanism through which creditworthiness factors influence bank policies. The detailed mediation analysis results are presented in Table 6, which provides a comprehensive summary of direct effects, indirect effects, total effects, and confidence intervals for both mediation pathways.

Table 6. Mediation analysis results

Mediation Path	Direct Effect	Indirect Effect	Total Effect	95% CI	Mediation Type
SCS → CBAEC → CBCP	0.285***	0.167***	0.452***	[0.112, 0.224]	Partial
CEI → CBAEC → CBCP	0.317***	0.193***	0.510***	[0.134, 0.257]	Partial

The mediation analysis reveals that both relationships demonstrate partial mediation effects. For SME credit status, the indirect effect through AI-enhanced cognition accounts for 37% of the total effect (0.167/0.452), while the direct effect remains significant. Similarly, for core enterprise influence, the indirect effect represents 38% of the total effect (0.193/0.510), also indicating partial mediation. These findings suggest that AI-enhanced cognition serves as an important but not exclusive pathway through which creditworthiness factors influence bank policies.

Moderation analysis revealed that AI assessment accuracy significantly strengthened the relationships between creditworthiness factors and bank policies. Hypothesis 5a was supported, showing that AI assessment accuracy positively moderated the relationship between SME credit status and credit policies ($\beta = 0.124$, $p < 0.001$). Multi-group analysis further demonstrated that banks with high AI assessment accuracy (one standard deviation above the mean) showed a stronger effect ($\beta = 0.396$) compared to those with low accuracy ($\beta = 0.198$). Hypothesis 5b was similarly supported, with AI assessment accuracy moderating the relationship between core enterprise influence and credit policies ($\beta = 0.138$, $p < 0.001$). The moderation effects were visualized through simple slope analysis, revealing that both relationships became progressively stronger as AI assessment accuracy increased. These findings underscore the critical role of AI system quality in amplifying the impact of traditional creditworthiness factors on bank lending decisions.

5. Discussion

This study provides empirical evidence for the transformative impact of AI-driven supply chain creditworthiness assessment on commercial banks' credit policies for SMEs. The research findings validate all proposed hypotheses, demonstrating that AI technology fundamentally changes traditional credit evaluation processes through multiple pathways. These findings align with Sadok et al. [17] regarding AI's transformative potential in banking credit systems, while building upon Xia et al. [18] who demonstrated superior accuracy of machine learning models in supply chain SME credit risk prediction. The results extend existing research by revealing specific mechanisms through which AI systems not only improve risk assessment accuracy but also enhance banks' cognitive capabilities to process complex supply chain information, leading to more favorable credit policies for qualified SMEs. The study advances AI-banking literature by identifying concrete cognitive and operational enhancements beyond general automation and technical accuracy discussions. The outcomes of the analysis demonstrate how the overall impact of enterprises is amplified through AI-enhanced evaluation frameworks. The research reveals that artificial intelligence allows banks to better leverage supply chain relationships in credit decisions, where the enterprise influence has a greater impact ($\beta = 0.317$) than the credit status of single SMEs ($\beta = 0.285$). The finding conforms to the contribution of Yin et al. [19], which proved that alternative information sources enhance SME credit risk measurement, whereas in this study, the measurement focuses on how AI systems integrate and leverage the dynamic nature of supply chain relationships. The research demonstrates a paradigm shift where AI systems effectively create a certification effect, allowing reputational capital from core enterprises to transfer to connected SMEs through quantifiable assessment metrics.

The study's most significant theoretical contribution lies in identifying AI-enhanced cognition as a critical mediating mechanism, accounting for 37-38% of the total effects in both key relationships. This finding reveals that AI's impact on credit policies operates through augmenting human cognitive capabilities in a hybrid decision-making model, supporting the human-AI collaboration perspective discussed by De Lange et al. [20] in banking contexts. Partial mediation effects are representative of the continued role of human judgment within credit decisions, even where AI supports banker cognition. The prominent moderating impact of AI evaluation precision ($\beta = 0.124$-0.138) captures the influence of system quality in strongly determining the efficacy of mapping credit policies, according to recent studies of AI system sophistication requirements [21]. The implications of these findings go beyond the boundaries of individual bank operations, affecting greater economic development and financial inclusion. The results show that creditworthiness assessment within supply chains through artificial intelligence represents a viable solution to the chronic financing shortage of small and medium-sized enterprises, as it shifts from collateral-based to relation-based evaluation. This finding contributes to the growing evidence of AI applications in various SME contexts, including recent work by Belhadi et al. [22] in agricultural SME credit risk prediction. The pronounced moderating effect of AI assessment accuracy suggests that continued technological advancement will amplify AI's impact in reducing information asymmetry within the financial industry. These findings provide empirical evidence that AI-augmented supply chain finance represents an effective strategy for narrowing the global financing gap for SMEs, promoting sustainable economic development, and enhancing supply chain resilience.

Despite these significant contributions, this study acknowledges several limitations that should be considered when interpreting the findings. The cross-sectional design primarily reveals associative relationships rather than strict causal relationships between variables. While the structural equation modeling approach provides evidence of directional relationships, the causal inference between AI assessment capabilities and changes in SME credit policies should be interpreted with caution, as causality cannot be definitively established without longitudinal data or experimental manipulation. The research sample, although covering six types of banks across five major cities, concentrates primarily in economically developed regions of China, which may limit the representativeness of findings to the broader Chinese banking landscape. The study is grounded in the Chinese banking environment, where regulatory frameworks, technology adoption patterns, and corporate cultures may differ significantly from international banking contexts, potentially limiting the transferability of findings to other institutional arrangements. The reliance on self-reported data may introduce response bias, as respondents' perceptions may not fully reflect objective organizational realities, despite employing Harman's single-factor test to assess common method bias. These limitations point toward several promising avenues for future research. Longitudinal studies could provide stronger evidence of causal relationships by tracking changes in bank credit policies before and after AI system implementation, offering insights into the dynamic evolution of AI-driven credit assessment impacts. Cross-national comparative studies would help validate the theoretical model's generalizability across different regulatory and cultural contexts, potentially revealing how institutional factors moderate the identified relationships. Mixed-methods approaches combining quantitative surveys with qualitative interviews could provide a deeper understanding of the mechanisms through which AI technology influences banker decision-making processes, offering richer insights into human-AI interaction dynamics in credit assessment contexts.

6. Conclusion

This research provides an empirical example focused on the impact of AI-enabled supply chain creditworthiness assessment and its effect on the credit policies of commercial banks regarding SMEs. As highlighted in the results, the main focuses of AI technology in the credit evaluation processes are: improved assessment of SMEs' credit status, more effective utilization of core enterprise relations, and enhancement of banks' cognitive capabilities to process intricate financial data. The importance of AI assessment accuracy particularly emphasises the degree of sophistication in technology needed to optimally attain such benefits developed by these systems. Providing evidence that AI systems can simultaneously improve access to credit for SMEs while adhering to the standards for risk management reinforces the argument for dualism in financial innovation. The study emphasises that the global SME financing gap can be narrowed by the advanced adoption of AI in supply chain finance, thus aiding sustainable economic development. It is recommended that the impact of AI on financial inclusion be studied extensively alongside the impact emerging technologies like blockchain and quantum computing could have on credit assessment within the scope of supply chain finance.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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Appendix G

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Title

The Impact of AI-Driven Supply Chain Creditworthiness Assessment on Comm ercial Banks' Credit Policies for SMEs

Authors

Wu Feng

Date of Editing

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