Future Technology
Open Access Journal
ISSN 2832-0379

August 2025| Volume 04 | Issue 03 | Pages 45- 53

Journal homepage: https://fupubco.com/futech

https://doi.org/10.55670/fpll.futech.4.3.5

Future Publishing LLC

Article

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

Feng Wu, Nusanee Meekaewkunchom*, Chaiyawit Muangmee, Tatchapong Sattabut

Bansomdejchaopraya Rajabhat University, Bangkok, Thailand

ARTICLE INFO

Article history:
Received 03 April 2025
Received in revised form
18 May 2025
Accepted 30 May 2025

Keywords:
AI-driven assessment, Supply chain finance, SME credit, Commercial banks, Creditworthiness evaluation

*Corresponding author
Email address:
Nusanee.me@bsru.ac.th

DOI: 10.55670/fpll.futech.4.3.5

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.

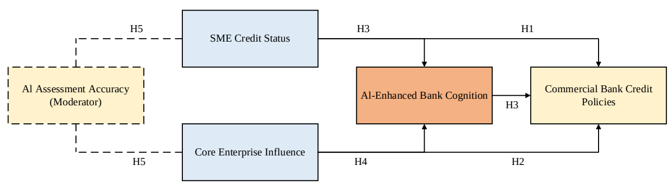

Figure 1. Research Framework

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.

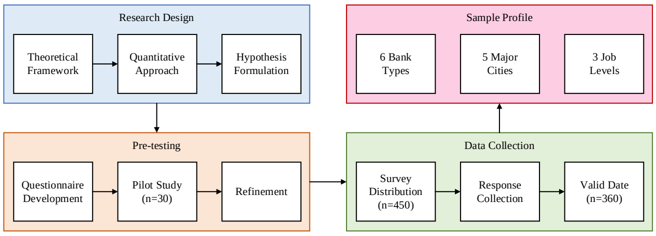

Figure 2. Research design and data collection process

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
SME Credit Status	SCS1	0.786	0.879	0.881	0.598
	SCS2	0.812			
	SCS3	0.798			
	SCS4	0.756			
	SCS5	0.731			
Core Enterprise Influence	CEI1	0.823	0.853	0.856	0.543
	CEI2	0.758			
	CEI3	0.719			
	CEI4	0.745			
	CEI5	0.703			
Commercial Bank Credit Policies	CBCP1	0.841	0.894	0.896	0.635
	CBCP2	0.829			
	CBCP3	0.807			
	CBCP4	0.785			
	CBCP5	0.749			
Commercial Bank AI-Enhanced Cognition	CBAEC1	0.846	0.887	0.889	0.617
	CBAEC2	0.812			
	CBAEC3	0.796			
	CBAEC4	0.773			
	CBAEC5	0.741			
AI Assessment Accuracy	AAA1	0.854	0.876	0.878	0.590
	AAA2	0.786			
	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 (β = 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 (β = 0.396) compared to those with low accuracy (β = 0.198). Hypothesis 5b was similarly supported, with AI assessment accuracy moderating the relationship between core enterprise influence and credit policies (β = 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 (β = 0.317) than the credit status of single SMEs (β = 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 (β = 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.

References

[1] L. Liu, J. Z. Zhang, W. He, and W. Li, "Mitigating information asymmetry in inventory pledge financing through the Internet of things and blockchain," Journal of Enterprise Information Management, vol. 34, no. 5, pp. 1429-1451, 2021. https://doi.org/10.1108/JEIM-12-2020-0510.

[2] S. Chen, D. R. Eyers, J. Gosling, and Y. Huang, "Supply chain risks for SMEs in construction projects: a structured literature review and research agenda," The International Journal of Logistics Management, 2025. https://doi.org/10.1108/IJLM-12-2023-0548.

[3] K. Wang, F. Yan, Y. Zhang, Y. Xiao, and L. Gu, "Supply chain financial risk evaluation of small-and medium-sized enterprises under smart city," Journal of advanced transportation, vol. 2020, no. 1, p. 8849356, 2020. https://doi.org/10.1155/2020/8849356.

[4] Y. Zhu, L. Zhou, C. Xie, G.-J. Wang, and T. V. Nguyen, "Forecasting SMEs' credit risk in supply chain finance with an enhanced hybrid ensemble machine learning approach," International Journal of Production Economics, vol. 211, pp. 22-33, 2019. https://doi.org/10.1016/j.ijpe.2019.01.032.

[5] L. Oldemeyer, A. Jede, and F. Teuteberg, "Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges," Management Review Quarterly, pp. 1-43, 2024. https://doi.org/10.1007/s11301-024-00405-4.

[6] S. Barja-Martinez, M. Aragüés-Peñalba, Í. Munné-Collado, P. Lloret-Gallego, E. Bullich-Massagué, and R. Villafafila-Robles, "Artificial intelligence techniques for enabling Big Data services in distribution networks: A review," Renewable and Sustainable Energy Reviews, vol. 150, p. 111459, 2021. https://doi.org/10.1016/j.rser.2021.111459.

[7] K. Jiang, X. Chen, J. Li, and M. Zhou, "Technology adoption and extreme stock risk: Evidence from digital tax reform in China," Humanities and Social Sciences Communications, vol. 12, no. 1, pp. 1-20, 2025. https://doi.org/10.1057/s41599-025-04483-x.

[8] N. Drydakis, "Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic," Information Systems Frontiers, vol. 24, no. 4, pp. 1223-1247, 2022. https://doi.org/10.1007/s10796-022-10249-6.

[9] F. Francesco and R. Tiziana La, "Does the bank-firm human relationship still matter for SMEs The game-changing role of digitalization," ed: Springer, 2023. https://doi.org/10.1007/s11187-023-00758-2.

[10] N. Madhavika et al., "Navigating economic crisis: Factors shaping resilience in Sri Lankan construction SME supply chains," International Journal of Construction Management, pp. 1-13, 2024. https://doi.org/10.1080/15623599.2024.2415158.

[11] S. Bakhtiari, R. Breunig, L. Magnani, and J. Zhang, "Financial constraints and small and medium enterprises: A review," Economic Record, vol. 96, no. 315, pp. 506-523, 2020. https://doi.org/10.1111/1475-4932.12560.

[12] W. Duan, H. Hu, and Y. Zhang, "What determines the performance of small and medium-sized enterprises supply chain financing? A qualitative comparative analysis of fuzzy sets based on the technology–organization–environment framework," Frontiers in psychology, vol. 13, p. 976218, 2022. https://doi.org/10.3389/fpsyg.2022.976218.

[13] J. Kaur, S. Kumar, and R. Joshi, "Is supply chain finance an antidote to SMEs in the economic crisis?-A

qualitative inquiry," The International Journal of Logistics Management, vol. 34, no. 6, pp. 1890-1910, 2023. https://doi.org/10.1108/IJLM-10-2021-0496.
[14] Z. Lou, Q. Xie, J. H. Shen, and C.-C. Lee, "Does supply chain finance (SCF) alleviate funding constraints of SMEs? Evidence from China," Research in International Business and Finance, vol. 67, p. 102157, 2024. https://doi.org/10.1016/j.ribaf.2023.102157.
[15] S. H. Bae, S. Saberi, M. Kouhizadeh, and J. Sarkis, "Examining blockchain's role in supply chain finance structure and governance," International Review of Financial Analysis, p. 103955, 2025. https://doi.org/10.1016/j.irfa.2025.103955.
[16] Q. Wang, S. Yuan, D. Ostic, and L. Pan, "Supply chain finance and innovation efficiency: An empirical analysis based on manufacturing SMEs," Plos one, vol. 18, no. 7, p. e0286068, 2023. https://doi.org/10.1371/journal.pone.0286068.
[17] H. Sadok, F. Sakka, and M. E. H. El Maknouzi, "Artificial intelligence and bank credit analysis: A review," Cogent Economics & Finance, vol. 10, no. 1, p. 2023262, 2022. https://doi.org/10.1080/23322039.2021.2023262.
[18] Y. Xia, T. Xu, M.-X. Wei, Z.-K. Wei, and L.-J. Tang, "Predicting chain's manufacturing SME credit risk in supply chain finance based on machine learning methods," Sustainability, vol. 15, no. 2, p. 1087, 2023. https://doi.org/10.3390/su15021087.
[19] C. Yin, C. Jiang, H. K. Jain, and Z. Wang, "Evaluating the credit risk of SMEs using legal judgments," Decision Support Systems, vol. 136, p. 113364, 2020. https://doi.org/10.1016/j.dss.2020.113364.
[20] P. E. De Lange, B. Melsom, C. B. Vennerød, and S. Westgaard, "Explainable AI for credit assessment in banks," Journal of Risk and Financial Management, vol. 15, no. 12, p. 556, 2022. https://doi.org/10.3390/jrfm15120556.
[21] M. El Khair Ghoujdam, R. Chaabita, O. Elkhalfi, K. Zehraoui, H. Elalaoui, and S. Idamia, "Consumer credit risk analysis through artificial intelligence: a comparative study between the classical approach of logistic regression and advanced machine learning techniques," Cogent Economics & Finance, vol. 12, no. 1, p. 2414926, 2024. https://doi.org/10.1080/23322039.2024.2414926.
[22] A. Belhadi, S. S. Kamble, V. Mani, I. Benkhati, and F. E. Touriki, "An ensemble machine learning approach for forecasting credit risk of agricultural SMEs' investments in agriculture 4.0 through supply chain finance," Annals of Operations Research, vol. 345, no. 2, pp. 779-807, 2025. https://doi.org/10.1007/s10479-021-04366-9.