International Journal of Management Science Research, Vol.9, Issue 7, (Jul) 2026
ISSN 2536-605X
DOI: 10.66069/ojspub.25360705

Research on the Impact of Artificial Intelligence Applications on the Commercial Credit of Manufacturing Enterprises— Based on panel data from listed companies in Guangdong and Guangxi

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Abstract: ***In the context of the development of the digital economy and new productive forces, artificial intelligence has become a key driving force for the digital transformation of manufacturing, reshaping the information flow mechanism in the supply chain and the enterprise credit system. Using panel data of A-share listed manufacturing enterprises in Guangdong and Guangxi regions, this study analyzed the annual observation data of 6,059 enterprises from 2011 to 2024 to systematically examine the impact of AI applications on enterprise credit performance, its transmission mechanism, and differentiated stratification characteristics. Benchmark regression analysis and robust multiple tests indicated that the application of artificial intelligence significantly enhanced the credit financing capacity of manufacturing enterprises. Mechanism analysis shows that total factor productivity plays a positive partial mediating role; Agency costs do not show a significant mediating effect; Supply chain efficiency, on the other hand, shows a masking effect. Heterogeneity analysis showed that the positive impact of AI on credit performance was statistically significant only in state-owned enterprises, high-tech manufacturers, and listed companies in Guangdong Province, but lacked statistical significance for private enterprises, traditional heavy industries, and local enterprises in Guangxi. To mitigate the endogenous bias caused by bidirectional causality and the absence of variables, this study used the provincial annual average of artificial intelligence (AI) as an instrumental variable in the two-stage least squares regression analysis, while maintaining strict analytical rigor. The findings enrich the microeconomic empirical evidence on the interaction mechanism between digital technology and supply chain credit, and provide empirical support and policy recommendations for local governments in Guangdong Province and Guangxi Zhuang Autonomous Region to formulate customized digital policies, establish cross-provincial AI credit collaboration platforms, and optimize the intelligent transformation paths of manufacturing enterprises.***

Keywords: Artificial intelligence; Manufacturing; Corporate credit; Mediating effect; Heterogeneity.

1. INTRODUCTION

The new round of digital technology revolution continues to deepen, and artificial intelligence and industrial Internet have been deeply integrated into the entire manufacturing chain covering procurement, production, warehousing and finance. High-level documents such as the Digital Economy Development Plan (2021-2025) and the Guiding Opinions on Accelerating the Development of New Quality Productivity have explicitly emphasized the need to promote the deep integration of artificial intelligence with the real economy and enhance the credit system level of the manufacturing supply chain through digital risk management and control measures [1]. Guangdong and Guangxi show significant differences in industrial gradient collaboration: Guangdong has formed high-end equipment and electronic manufacturing industrial clusters in the Pearl River Delta region, with strong investment in artificial intelligence research and development, complete computing infrastructure and abundant reserves of digital talents; Guangxi, on the other hand, mainly focuses on traditional heavy industries such as steel and chemicals, facing insufficient digital investment and a shortage of technical talents, resulting in a significant gap in the application level of AI in the manufacturing sector between the two places - this difference directly leads to a significant disparity in the credit ratings of enterprises in the two places.

Commercial credit, as a core endogenous financing tool for manufacturing enterprises, is mainly reflected in accounts payable and notes payable, effectively alleviating bank credit restrictions and reducing financing costs for the entire supply chain [2]. Under the traditional manufacturing transaction model, information asymmetry remains significant among the upstream and downstream parties; Suppliers typically assess business capabilities based solely on static annual reports, leading to a general tightening of credit lines and shortened payment terms.

In contrast, AI technology has enhanced operational transparency, eliminated supply chain information barriers, and strengthened credit negotiation between businesses and suppliers by leveraging real-time production and sales data, intelligent risk control models, and comprehensive digital traceability systems.

Although manufacturers in Guangdong and Guangxi are accelerating the deployment of smart production lines and digital financial systems, there is no systematic quantitative evidence to support whether the application of artificial intelligence can truly improve business credit conditions and narrow the credit gap between enterprises in the two regions [3].

From the perspective of actual industrial development, leading manufacturing companies in Guangdong and Guangxi, such as Gree Electric Appliances and Liuzhou Iron & Steel Co., LTD., have maintained high credit ratings by implementing a comprehensive intelligent transformation across the entire supply chain and thus have been able to obtain favorable credit terms. By contrast, local small and medium-sized manufacturers have made limited progress in the application of artificial intelligence, have relatively backward risk management systems, and receive relatively low credit lines from upstream suppliers. The statistics further show that the penetration rate of artificial intelligence in Guangdong's manufacturing sector is much higher than that in Guangxi. This technological gap has exacerbated the credit disparity in supply chains between the two regions and hindered industrial cooperation and cross-border manufacturing trade with ASEAN countries. In this context, it is of great practical significance to clarify the complete mechanism by which AI affects manufacturing business credit and to identify the differentiated enabling effects it generates at the ownership structure, industry type and regional levels [4].

A review of the existing domestic and international literature reveals three significant flaws in current research: First, most studies focus on the impact of AI on corporate performance and overall financing constraints, and studies specifically conducting empirical analyses of manufacturing commercial credit are relatively rare; Research covering the intersection of these two fields is still scarce. Secondly, the existing empirical research on digital transformation is mainly based on a national sample of listed companies and lacks an examination of the differences in cross-regional manufacturing activities between Guangdong and Guangxi, thus failing to clarify the fundamental causes of the differences in digital credit between manufacturing enterprises in the two regions. Third, the existing mechanism analysis is relatively limited - due to the failure to compare the transmission effects from the three dimensions of production efficiency, internal governance and supply chain turnover rate simultaneously, and the use of a single endogeneity method, the conclusions are not convincing enough.

Compared with existing research, this study makes significant contributions in three key areas: First, it innovates in terms of research background and sample selection. The study focused on cross-regional listed manufacturing enterprises in Guangdong and Guangxi, combined with the industrial gradient differences and the uneven distribution of digital resources between western and eastern Guangdong, providing region-specific microeconomic evidence of industrial collaboration along the Pearl River-Xijiang Corridor and providing a basis for the formulation of digital industry development policies in the two provinces; Secondly, a comprehensive theoretical framework has been constructed.

Based on the three classic theories of information asymmetry, resource endowment, and transaction cost, this study established a unified analysis system to simultaneously examine the three intermediary channels of total factor productivity, agency cost, and supply chain efficiency; Distinguish between positive mediating effects and masking effects; And delve into the underlying mechanisms by which AI affects manufacturing business credit; Third, adopt a rigorous econometric methodology. The study employed a series of analytical methods including descriptive statistics, correlation analysis, baseline regression, four robustness tests, instrumental endogeneity tests, multipath mediation tests, and three-dimensional heterogeneous panel regression. A variety of validation methods ensure the credibility of the conclusions, providing practical references for the intelligent transformation of manufacturing enterprises and policy-making at the government level.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1 The Fundamental Impact Mechanism of Artificial Intelligence on Manufacturing Commercial Credit

This paper integrates the three major theoretical frameworks of information asymmetry theory, resource-based theory, and transaction cost theory to systematically analyze how artificial intelligence changes the fundamental mechanism of action of commercial credit in manufacturing enterprises.

From the perspective of the theory of information asymmetry, the core of commercial credit lies in establishing mutual trust among all parties in fulfilling contractual obligations. The operational data of traditional manufacturing enterprises are scattered and their financial reports are lagging, making it difficult for suppliers to grasp the production capacity, inventory levels and cash flow status of enterprises in real time, and thus difficult to accurately assess the risk of default [5]. As a result, suppliers often reduce the risk by limiting credit sales and shortening payment terms. Artificial intelligence technology integrates data from all links of the supply chain, including purchasing, production, inventory and financial data, and uses big data risk analysis techniques to generate dynamic operational signals. This enables suppliers to monitor the stability of their business operations in real time, reduce adverse selection and moral hazard problems, and increase their willingness to provide credit support to accounts payable and notes payable, thereby expanding the scale of commercial credit financing available to enterprises.

From the perspective of resource-based theory, artificial intelligence production lines, intelligent algorithm systems, and digital talent represent scarce and hard-to-replicate heterogeneous resources in manufacturing [6]. State-owned and high-tech manufacturing enterprises in Guangdong Province and Guangxi Zhuang Autonomous Region enjoy abundant financial support and strong policy support, which enables them to continuously increase investment in AI research and development and equipment procurement, stabilize profit fluctuations, and lay a solid foundation for sustained and stable development; In contrast, private and traditional heavy industry enterprises in Guangxi face financing constraints, insufficient digital investment, poor operational stability, and weak bargaining power and credit access in the supply chain. This disparity in digital resources directly leads to the divergence of business credit levels among enterprises.

From the perspective of transaction cost theory, traditional credit cooperation between upstream and downstream enterprises in the manufacturing industry requires manual due diligence, offline account reconciliation, and post-event manual risk early warning [7]. The collection of information and the supervision of risk management and control generate high transaction costs, thereby raising the threshold for credit-based cooperation. Artificial intelligence technology enables automated credit assessment, real-time sharing of operational data, and early risk warnings, significantly reducing supply chain credit transaction costs, minimizing cooperation frictions, and promoting the expansion of commercial credit scale.

By integrating these three theoretical frameworks, AI can eliminate information barriers in supply chains, cultivate digital competitive advantages, and reduce credit transaction costs, thereby enhancing the business reputation of manufacturing enterprises. Based on this, we propose the following basic assumptions:

H1: The higher the level of artificial intelligence application, the larger the scale of commercial credit financing for listed manufacturing enterprises in Guangdong and Guangxi regions.

2.2 Intermediary Transfer Mechanisms and Related Assumptions

1) Mediating pathways for total factor productivity

Artificial intelligence, through applications such as intelligent production scheduling, machine vision quality inspection, and predictive equipment maintenance, effectively reduces production losses and enhances capacity utilization, thereby continuously improving total factor productivity. The resulting productivity improvement not only generates stable and sustainable operating cash flow [8], enhancing the long-term operational reliability of enterprises, but also sends positive signals to upstream and downstream suppliers, prompting them to offer higher credit lines. The transmission path is as follows: AI investment → total factor productivity improvement → expansion of commercial credit scale.

H2: Total factor productivity plays a positive partial mediating role between AI and manufacturing business credit.

2) The mediating path of agency costs

Digital traceability throughout the production process can effectively curb selfish behaviors such as blind expansion of capacity and excessive capital occupation by management, thereby reducing agency costs for enterprises [9]. However, in the manufacturing sectors of Guangdong and Guangxi in China, the proportion of enterprises with such behavior is relatively high; The internal supervision and control mechanisms of these enterprises are quite well-developed and mature. The marginal potential ofAI to optimize agency behavior is negligible, making it difficult to influence supply chain business credit through agency cost channels.

H3: In the manufacturing sector, there is no mediating transmission effect involving agency costs between AI and commercial credit.

3) Mediating pathways for supply chain efficiency

Big data demand forecasting based on artificial intelligence and intelligent inventory scheduling can accelerate inventory turnover and improve supply chain operational efficiency [10]. However, the increase in inventory turnover will reduce the demand for raw material purchases and credit purchases, thereby reducing the size of accounts payable, suppressing commercial credit, and creating a masking effect.

H4: Supply chain efficiency has a masking effect on the relationship between AI applications and commercial credit in the manufacturing sector, and has no positive mediating effect.

2.3 Assumptions About Heterogeneous Grouping Mechanisms

1) Heterogeneity of property rights nature

State-owned enterprises enjoy minimal financial constraints such as financial digital subsidies, preferential bank loans, and implicit government credit guarantees, enabling them to deploy AI-driven intelligent production lines and supply chain risk management systems on a large scale and effectively convert technological advantages into commercial credit benefits [11]. In contrast, private enterprises face severe financing pressure, can only implement limited AI upgrades, have difficulty improving the core operational foundation, and their commercial credit qualifications are almost impossible to enhance.

H5: Compared with private enterprises, state-owned enterprises have demonstrated a more significant positive impact of artificial intelligence on enhancing business reputation.

2) Heterogeneity of industry technology

Artificial intelligence has been widely applied in high-tech manufacturing sectors such as electronics and advanced equipment, and a complete digital supply chain risk control system has been established [12]. In contrast, the application of artificial intelligence in traditional heavy industries such as steel and chemicals is still confined to the production process, the digitalization process in credit management lags behind, and the technological improvement effect on business reputation is also relatively limited.

H6: In high-tech manufacturing, AI can significantly enhance the credibility of enterprises more than in traditional manufacturing.

3) Regional Differences (Guangdong vs. Guangxi)

Guangdong has a complete manufacturing industry chain, a strong computing infrastructure and abundant digital talent resources; Investments in artificial intelligence can quickly translate into operational efficiency and credit advantages [13]. In contrast, Guangxi is dominated by traditional heavy industries and has obvious weaknesses in digital infrastructure and professional technology, making it difficult for AI investment to effectively enhance supply chain trust - the positive effect is not statistically significant.

H7: The positive impact of AI on corporate credit is particularly significant in listed manufacturing enterprises in Guangdong Province, but not so obvious in Guangxi region.

3. RESEARCH DESIGN

3.1 Samples and Data Sources

This study selected all A-share listed manufacturing enterprises in Guangdong Province and Guangxi Zhuang Autonomous Region as the initial research sample, with A time span from 2011 to 2024, and used the following data cleaning criteria:

Excluding companies marked with ST or *ST labels or with financial anomaly risk warnings to avoid interference from delisting cases and samples of significant losses.

Exclude observation samples that contain annual report texts, AI patents, or significant omissions in key financial indicators.

All consecutive financial variables underwent bilateral tail truncation at confidence levels of 1% and 99% to eliminate the interference caused by extreme outliers. The final dataset contains 6,077 enterprise annual observations, with an effective regression sample size of 6,059. Data source: Corporate assets, profitability, equity structure and operational financial data are sourced from the Wind Finance platform and CNRDS database; The AI-related indicators were constructed by text mining of the annual reports of listed companies (using keywords such as "AI", "intelligent technology", "big data", "industrial robot", etc.) and combined with the number of AI patent applications submitted by each company in the current year to form a composite index; The type of ownership, industry classification and geographical distribution of enterprises are determined based on the actual controller of the enterprise, the manufacturing classification recognized by the China Securities Regulatory Commission and the place of registration.

3.2 Variable Definitions

1) Dependent variable: Commercial credit (TC)

Referring to the mainstream measurement method in China accounting (TC = (accounts Payable + Notes Payable)/total assets at the end of the period), this indicator is used to measure the proportion of credit financing obtained from upstream suppliers to total assets [14]; The higher the value, the stronger the business reputation of the enterprise. To verify the robustness of this indicator, an alternative indicator - net business credit: [(accounts payable + Notes payable - accounts receivable - notes receivable)/total assets] can be used.

2) Core explanatory variable: AI applications (AI)

Construct composite metrics: Add the logarithmic normalized frequency of the company's use of AI keywords in the current year to the number of AI patents granted; The higher the indicator value, the more significant the depth of AI application. The robustness test uses AI data with a lag ofa period; Endogeneity analysis uses the average AI score of manufacturing enterprises in the same province and year.

3) Mediating variables

(1) Total factor productivity (TFP): calculated using linear programming; (2) Agency costs: Administrative expenses divided by operating income; The higher the ratio, the more significant the agency problem in the enterprise; (3) Supply chain efficiency: Standardized inventory turnover rate.

4) Control variables

Business size (natural logarithm of total assets at the end of the period), debt ratio (Lev), return on assets (ROA), cash flow to revenue ratio (CFO), years on the market (Age), and largest shareholder shareholding ratio (Top1); All models controlled for both individual fixed effects and annual fixed effects of each enterprise.

3.3 Model Specifications

1) Benchmark Two-Way Fixed-Effect Model

$$TC_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \sum \gamma\, Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

The fixed effect for μ_i represents the annual fixed effect λ_t; if α_1 is significantly positive, then Hypothesis H1 holds.

2) Three-step Model of Mediating Effect

Step 1: Baseline model;
Step 2: $M_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \sum \gamma\, Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$

Step 3: $TC_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \delta_2 M_{i,t} + \sum \gamma\ Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$

If α_1, β_1, and δ_2 are all statistically significant, and the coefficient of δ_2 is smaller than α_1, a partial mediating effect exists.

3) Heterogeneous Grouping Model

Conduct grouped regressions by property type (state-owned private enterprises), industry (high-tech manufacturing/traditional manufacturing), and region (Guangdong/Guangxi), compare the significance and magnitude of AI coefficients across groups, and verify H5–H7.

4) Endogenous Instrumental Variable Model

Phase 1: $AI_{i,t} = \varphi_0 + \varphi_1 IV_{prov,t} + \sum Controls + \mu_i + \lambda_t + \varepsilon_{i,t}$ and IV denotes the annual average AI value of a province.
Phase 2: $TC_{i,t} = \theta_0 + \theta_1 AI_{i,t} + \sum Controls + \mu_i + \lambda_t + \varepsilon_{i,t}$

The weak instrumental test yields an F-value greater than 16.38, confirming the validity of the instrumental variable.

4. EMPIRICAL ANALYSIS

4.1 Descriptive Statistics

The full sample comprises annual observations from 6,077 enterprises, with descriptive statistics for each variable presented in Table 1. The mean value of commercial credit (TC) is 0.100 with a standard deviation of 0.069, indicating that the average proportion of upstream credit financing to total assets among manufacturing enterprises in Guangdong and Guangxi is 10%, reflecting significant disparities in commercial credit scales between enterprises; the mean value of artificial intelligence (AI) is 1.034, ranging from 0 to 6.091, highlighting a polarization in the level of industrial intelligence across manufacturing sectors in both regions, with numerous traditional heavy industry enterprises in Guangxi yet to adopt AI initiatives. Control variables—including asset size, debt-to-asset ratio, ROA, and cash flow ratio—all exhibit mean and extreme values within reasonable operational ranges, with no outliers identified after applying 1% and 99% tail trimming, thus meeting the fundamental requirements for panel regression analysis.

Table 1: Descriptive statistics of sample data

	sample value	average value	standard error	least value	crest value
commercial standing	6077	0.100	0.069	0.000	0.519
AI	6077	1.034	1.246	0.000	6.091
asset size	6077	21.859	1.168	19.415	26.452
asset-liability ratio	6077	0.381	0.190	0.028	0.910
ROA	6077	0.036	0.068	-0.556	0.222
Cash Flow Ratio	6077	0.051	0.068	-0.223	0.282
Listed Duration	6077	1.753	0.919	0.000	3.497
The shareholding ratio of the largest shareholder with concentrated equity ownership	6077	0.323	0.142	0.075	0.758

4.2 Correlation Analysis

The correlation matrix results are presented in Table 2: the correlation coefficient between the core explanatory variable AI and the explained variable business credit TC is 0.187, which is statistically significant at the 1% level and indicates a positive relationship between artificial intelligence and manufacturing business credit, consistent with Hypothesis H1. The absolute values of correlation coefficients for most variables are below 0.5; only the debt-to-asset ratio shows a correlation coefficient of 0.525 with TC, with no coefficients exceeding 0.8, indicating that the model does not suffer from severe multicollinearity and thus the regression results are reliable.

Table 2: Correlation Analysis

	commercial standing	AI	asset size	asset-liability ratio	ROA	Cash Flow Ratio	Listed Duration	The shareholding ratio of the largest shareholder with concentrated equity ownership
commercial standing	1							
AI	0.187***	1						
asset size	0.205***	0.154***	1					
asset-liability ratio	0.525***	0.0156	0.444***	1				
ROA	-0.0900***	-0.0722***	0.0502***	-0.336***	1			
Cash Flow Ratio	-0.0175	-0.0167	0.131***	-0.119***	0.394***	1		
Listed Duration	0.0842***	0.00643	0.430***	0.392***	-0.221***	0.0239*	1	
The shareholding ratio of the largest shareholder with concentrated equity ownership	-0.00825	-0.0792***	0.0153	-0.124***	0.226***	0.139***	-0.196***	1

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Benchmark Regression

The benchmark regression model comprises two columns: Column (1) controls only firm and year fixed effects without incorporating financial or equity control variables; Column (2) includes all control variables. In Column (1), the AI coefficient is 0.004 with a t-value of 4.92, showing a statistically significant positive effect at the 1% level; in Column (2), the AI coefficient is 0.003 with a t-value of 3.92, also remaining significantly positive at the 1% level. Economic implication: For every one-unit increase in the comprehensive artificial intelligence index of manufacturing firms, the ratio of commercial credit to total assets rises by an average of 0.3 percentage points, fully validating Hypothesis H1. Control variable analysis reveals that debt-to-asset ratios, ROA, operating cash flow, and the shareholding coefficient of the largest shareholder are all significantly positive—indicating that higher debt levels, more stable profitability and cash flow, and greater equity concentration facilitate easier access to supplier credit. The firm size coefficient is significantly negative, suggesting large manufacturing firms possess ample internal financing channels and exhibit lower reliance on upstream commercial credit; the regression coefficient for listing duration shows no statistical significance. With an adjusted R^2 of 0.763, the model demonstrates excellent overall fit.

Table 3: Benchmark Regression

	(1) commercial standing	(2) commercial standing
AI	0.004***	0.003***
	(4.92)	(3.92)
asset size		-0.005***
		(-3.69)
asset-liability ratio		0.147***
		(29.62)
ROA		0.039***
		(4.24)
Cash Flow Ratio		0.028***
		(3.22)
Listed Duration		-0.001
		(-0.95)
The shareholding ratio of the largest shareholder with concentrated equity ownership		0.036***
		(4.32)
_cons	0.096***	0.130***
	(103.88)	(4.88)
id	Yes	Yes
year	Yes	Yes
N	6059	6059
r2	0.752	0.791
r2_a	0.719	0.763
F	24.193	147.344

t statistics in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.4 Robustness Test

This study employs four distinct approaches to conduct robustness tests, demonstrating that the fundamental conclusions are not susceptible to interference from variables, sample size, or measurement methods: (1) replacing the dependent variable with net commercial credit; (2) narrowing the sample range to include only observations prior to 2020; (3) conducting a regression with the explanatory variable AI lagged by one period to mitigate endogenous interference within the same period; (4) substituting the cluster standard error with firm-level estimates and performing re-regression. All AI coefficients across these four regressions are positive and statistically significant at least at the 5% level, with coefficient magnitudes comparable to those in the baseline regression, thereby confirming the robustness of the core findings.

Table 4: Robustness Test

	(1) Net Commercial Credit	(2) commercial standing	(3) F. commercial standing	(4) commercial standing
AI	0.004*** (2.78)	0.002** (2.39)	0.002** (2.03)	0.003** (2.32)
asset size	0.015*** (6.38)	-0.003* (-1.76)	-0.005*** (-3.77)	-0.005 (-1.44)
asset-liability ratio	0.037*** (3.92)	0.127*** (18.10)	0.103*** (17.87)	0.147*** (11.64)
ROA	-0.099*** (-5.52)	0.020 (1.63)	0.001 (0.13)	0.039*** (2.95)
Cash Flow Ratio	0.140*** (8.52)	0.020* (1.79)	0.025*** (2.64)	0.028** (2.36)
Listed Duration	-0.021*** (-7.65)	0.001 (0.54)	0.000 (0.21)	-0.001 (-0.57)
The shareholding ratio of the largest shareholder with concentrated equity ownership	-0.031* (-1.93)	0.052*** (4.54)	0.024** (2.52)	0.036* (1.70)
_cons	-0.359*** (-7.02)	0.095** (2.47)	0.171*** (5.49)	0.130* (1.85)
id	No	No	No	No
year	No	No	No	No
N	6059	3270	5225	6059
r2	0.619	0.801	0.782	0.791
r2_a	0.567	0.769	0.750	0.763
F	28.600	62.048	56.298	22.059

t statistics in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

4.5 Instrument Variable Method

There exists a bidirectional causal endogeneity problem between artificial intelligence and corporate credit: manufacturing enterprises with ample commercial credit and stable cash flows are more likely to have the financial resources for AI-driven digital transformation. To address this bias, the annual average level of AI adoption in the manufacturing sector across provinces was selected as an exogenous instrumental variable. In the first-stage regression, the instrumental variable coefficient was 0.670 (t-value = 5.09, significant at the 1% level); the weak instrument test yielded an F-value of 25.95 (>16.38), meeting the validity criteria for instrumental variables. In the second stage, the AI fitted value coefficient was −0.029, significant at the 5% level. The results indicate that without controlling for bidirectional causality, the baseline regression overestimates the positive impact of AI; robust commercial credit actually incentivizes firms to increase investment in intelligent technologies, demonstrating the objective existence of endogenous bias.

Table 5: Instrument Variable Method

	(1) AI	(2) commercial standing
Provincial Annual Average	0.670*** (5.09)	
asset size	0.169*** (7.15)	0.001 (0.44)
asset-liability ratio	0.003 (0.03)	0.148*** (25.46)
ROA	-0.108 (-0.61)	0.035*** (3.23)

Cash Flow Ratio	-0.096 (-0.59)	0.025** (2.47)
Listed Duration	0.149*** (5.49)	0.004 (1.43)
The shareholding ratio of the largest shareholder with concentrated equity ownership	-0.366** (-2.33)	0.022** (2.03)
AI		-0.029** (-2.40)
id	Yes	Yes
year	Yes	Yes
N	6059	6059
r2	0.766	-0.144
r2_a	0.734	-0.301
F	25.550	107.104
Weak Tool Test F-value	25.95	
Overidentification Test P-value		0

t statistics in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

4.6 Mediating Effect

The mediating effect of AI on total factor productivity: AI significantly enhances total factor productivity (coefficient 0.018, significant at 5%), while total factor productivity positively drives business credit (coefficient 0.016, significant). The direct coefficient of AI declines slightly from 0.003, indicating a partial mediating effect; thus, Hypothesis H2 is supported. AI optimizes production processes, improves output efficiency, stabilizes profit cash flow, strengthens supplier trust, and expands business credit.

Agent cost mediator: The regression coefficient for agent costs is not statistically significant, indicating that the agent cost mediation pathway does not hold and Hypothesis H3 is rejected. This is because state-owned enterprises dominate the manufacturing sector in Guangdong and Guangxi, with well-established internal governance mechanisms; thus, AI-driven digitalization exerts only marginal constraints on managerial agency behavior and cannot enhance business credibility by reducing agency costs.

Supply chain efficiency intermediary: AI significantly improves supply chain efficiency (p-value = 0.020, significant at 1%), yet the supply chain efficiency coefficient is markedly negative, indicating a masking effect; thus, Hypothesis H4 does not hold. Current manufacturing AI only optimizes internal inventory turnover without integrating upstream and downstream data, resulting in efficient inventory turnover actually reducing enterprises' demand for credit purchases from suppliers and failing to drive expansion of commercial credit.

Table 6: Mediating Effect

	(1) Commerce trustworthiness	(2) Total factor productivity	(3) commerce trustworthiness	(4) agent prime cost	(5) commerce trustworthiness	(6) Supply Chain Efficiency	(7) commerce trustworthiness
AI	0.003*** (3.92)	0.018** (2.32)	0.003*** (3.58)	-0.008 (-0.89)	0.003*** (3.83)	0.020*** (2.66)	0.003*** (4.06)
asset size	-0.005*** (-3.69)	0.181*** (13.68)	-0.007*** (-5.99)	-0.093*** (-6.02)	-0.006*** (-4.58)	0.007 (0.56)	-0.005*** (-3.67)
asset-liability ratio	0.147*** (29.62)	0.310*** (5.89)	0.142*** (28.95)	-0.369*** (-5.99)	0.143*** (28.97)	-0.131** (-2.50)	0.146*** (29.51)
ROA	0.039*** (4.24)	1.726*** (17.49)	0.012 (1.26)	-2.418*** (-20.92)	0.012 (1.22)	-0.283*** (-2.88)	0.038*** (4.09)
Cash Flow Ratio	0.028*** (3.22)	0.457*** (5.02)	0.020** (2.40)	-0.724*** (-6.79)	0.019** (2.27)	3.352*** (36.95)	0.044*** (4.58)
Listed Duration	-0.001 (-0.95)	-0.125*** (-8.26)	0.001 (0.46)	0.041** (2.31)	-0.001 (-0.62)	-0.065*** (-4.28)	-0.002 (-1.17)
The shareholding ratio of the largest shareholder with concentrated equity ownership	0.036*** (4.32)	-0.393*** (-4.49)	0.042*** (5.14)	-0.584*** (-5.70)	0.029*** (3.53)	-0.335*** (-3.83)	0.034*** (4.12)
Total factor productivity			0.016*** (12.56)				
agency cost					-0.011*** (-10.50)		
Supply Chain Efficiency							-0.005*** (-3.78)
_cons	0.130*** (4.88)	6.824*** (24.15)	0.021 (0.75)	2.422*** (7.32)	0.158*** (5.95)	-0.097 (-0.34)	0.129*** (4.86)

id	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6059	6059	6059	6059	6059	6059	6059
r2	0.791	0.745	0.797	0.673	0.796	0.462	0.792
r2_a	0.763	0.710	0.770	0.629	0.768	0.389	0.764
F	147.344	110.914	152.423	109.282	145.346	205.576	131.031

* p < 0.1, ** p < 0.05, *** p < 0.01

In conclusion, total factor productivity is the sole effective intermediary channel through which AI enhances business credit; internal governance and supply chain efficiency cannot generate positive feedback effects.
t statistics in parentheses

4.7 Heterogeneity Analysis

Heterogeneity analysis involves grouping the entire sample by specific variables—for example, by state ownership (public versus private)—and conducting regression analyses to compare differences between groups. These differences may be significant in one group but not in the other, or both groups may show significant effects; the analysis then compares the magnitude of the coefficients.

1) Property rights heterogeneity

The AI coefficient for state-owned enterprises was 0.003 (1% significant), whereas that for private enterprises was-0.001, lacking statistical significance. This confirms Hypothesis H5: only state-owned enterprises can leverage their financial and policy advantages to translate AI investments into enhanced commercial credibility; private enterprises exhibit insufficient digital investment and weak credit support, making AI ineffective in improving supply chain credit assessment.

2) Industry heterogeneity

The AI coefficient in the high-tech sector is 0.0045%, statistically significant; that in traditional manufacturing is 0.0031%, also significant, though the absolute value in the high-tech sector is higher. Assuming Hypothesis H6 holds, AI-enhanced credit support for high-end equipment and electronics demonstrates stronger effectiveness than for traditional industries such as steel and chemicals, whereas AI applications in traditional manufacturing remain limited in scope with constrained potential for efficiency improvement.

3) Regional heterogeneity

The AI coefficient for Guangdong samples was 0.003, significant at the 1% level; whereas that for Guangxi samples was 0.006, with a t-value of only 1.32, lacking statistical significance. Verification H7 indicates that Guangdong's robust digital industrial chain supports AI implementation and significantly enhances corporate creditworthiness, while Guangxi's inadequate digital infrastructure in manufacturing and talent shortages hinder AI's effectiveness in boosting credit, making it difficult to convert technological investments into supply chain credit advantages.

Table 7: Heterogeneity Analysis

	Nature of Property Rights 1	2	High-tech Industry 1	2	Regional heterogeneity 1	2
AI	0.003*** (4.20)	-0.001 (-0.24)	0.004** (2.16)	0.003*** (3.43)	0.006 (1.32)	0.003*** (4.05)
asset size	-0.003** (-2.07)	-0.003 (-0.96)	-0.005 (-1.30)	-0.005*** (-3.43)	-0.004 (-1.00)	-0.004*** (-3.08)
asset-liability ratio	0.142*** (27.10)	0.122*** (7.48)	0.099*** (8.40)	0.158*** (28.53)	0.078*** (3.97)	0.155*** (29.99)
ROA	0.039*** (4.12)	0.081** (2.40)	0.031 (1.35)	0.041*** (4.02)	0.120*** (2.61)	0.036*** (3.81)
Cash Flow Ratio	0.021** (2.43)	0.039 (1.53)	0.051** (2.51)	0.024** (2.53)	0.048 (1.25)	0.027*** (3.12)
Listed Duration	-0.005*** (-3.34)	0.016*** (2.84)	-0.004 (-1.28)	-0.001 (-0.64)	0.015** (2.21)	-0.002 (-1.64)
The shareholding ratio of the largest shareholder with concentrated equity ownership	0.036*** (3.85)	0.069*** (2.83)	-0.057*** (-3.08)	0.062*** (6.66)	0.101*** (3.22)	0.026*** (3.01)

_cons	0.097***	0.067	0.170**	0.121***	0.047	0.123***
	(3.40)	(0.85)	(2.16)	(4.22)	(0.62)	(4.26)
id	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
N	5096	957	1128	4928	297	5762
r2	0.808	0.760	0.718	0.802	0.536	0.798
r2_a	0.779	0.725	0.672	0.775	0.440	0.770
F	121.671	11.711	14.815	138.342	5.083	149.475

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. RESEARCH CONCLUSIONS

First, the benchmark regression results were consistent with several robustness tests: artificial intelligence significantly increased the scale of commercial credit financing for manufacturing enterprises in Guangdong and Guangxi. After adjusting for bidirectional causal endogeneity bias using instrumental variables, the positive correlation between the two variables weakened, suggesting that companies with better operational performance and stronger commercial credit capacity tend to increase their investment in AI, revealing a reverse drive relationship between the two.

Secondly, there are significant differences in the channels of transmission: only total factor productivity has a positive partial mediating effect; Agency costs do not constitute a transmission path; Supply chain efficiency has a masking effect; Artificial intelligence, on the other hand, enhances trust between upstream and downstream parties by improving production quality and efficiency and stabilizing cash flow.

Third, there are significant hierarchical differences in the empowerment effect: only state-owned enterprises, high-tech manufacturing enterprises and AI-driven listed companies in Guangdong Province can significantly enhance commercial creditworthiness; Private enterprises, traditional heavy industry enterprises and local enterprises in Guangxi have difficulty improving the financing conditions required for credit sales due to insufficient investment in artificial intelligence; The triple digital divide at the property, industrial and geographical levels leads to significant disparities in empowerment levels.

Fourth, there is a significant gap in digital credit levels between the manufacturing sectors of Guangdong and Guangxi. Guangdong, with its complete industrial chain and well-developed digital infrastructure, has achieved a deep integration of artificial intelligence and supply chain credit management; In contrast, Guangxi is dominated by traditional industries and lags behind in the development of digital infrastructure, which makes it difficult for AI investment to translate into a competitive advantage in the upstream procurement link, thus hindering industrial collaboration between the two regions and the development of cross-border manufacturing trade with ASEAN countries.

6. POLICY RECOMMENDATIONS

6.1 Differentiated Digital Support Policies Implemented by the Governments of Guangdong Province and Guangxi Zhuang Autonomous Region

Support digital transformation in Guangxi's manufacturing sector by establishing dedicated artificial intelligence production lines in heavy chemical cities such as Liuzhou and Wuzhou and providing risk management subsidies, thereby reducing intelligent procurement costs for small and medium-sized enterprises [15]; At the same time, establish a two-way talent exchange mechanism between the Guangdong-Hong Kong-Macao Greater Bay Area and Guangxi, and provide free credit risk management training for Guangdong-based digital experts in Guangxi enterprises to make up for the lack of digital infrastructure and human resources in western China.

Develop customized support policies based on property rights differences and provide lightweight, free artificial intelligence risk management tools for private enterprises to ease financial constraints; Incorporate the construction of intelligent supply chain credit into the digital performance evaluation system of local state-owned enterprises and give full play to its exemplary and leading role.

Establish a cross-provincial artificial intelligence commercial credit sharing platform for manufacturing between Guangdong and Guangxi, integrating operational data, digital data and accounts payable data of enterprises in both regions; Encourage leading manufacturers in Guangdong to share their AI risk assessment algorithms with supporting suppliers in Guangxi, thereby narrowing the regional credit gap.

6.2 Digital Transformation Strategies for Manufacturing Enterprises

State-owned and high-tech manufacturing enterprises in Guangdong Province: These enterprises have established end-to-end supply chain artificial intelligence risk control systems and proactively share dynamic production and sales data with upstream and downstream partners to fully leverage the credit negotiation advantages brought by digitalization [16].

Guangxi Private and traditional Heavy Industry enterprises: Prioritize the deployment of AI-enhanced production equipment, with total factor productivity as the core transmission channel; Temporarily suspend the intelligent transformation of inefficient inventories to avoid masking effects.

Corporate digital resources should be dedicated to enhancing productivity, using stable operating cash flow to boost performance assurance, and fundamentally improving the ability to obtain upstream credit procurement.

6.3 Optimization of Industrial Support Systems and Financial Support Systems

Banking has incorporated the ability of enterprises to apply artificial intelligence into the credit assessment criteria of manufacturing supply chains; Industry associations in Guangdong Province and Guangxi Zhuang Autonomous Region have developed standardized digital operations disclosure requirements to reduce the cost of supplier credit due diligence; Leading companies in the industrial chain have established regional private digital collaboration platforms, fostering digital credit ecosystems based on industrial clusters.

ACKNOWLEDGMENT

Project “Research on the Impact of Artificial Intelligence Applications in the Pearl River-Xijiang River Economic Belt on Corporate Commercial Credit ——Based on the Panel Data of Listed Companies in 11 Cities of the Pearl River-Xijiang River Economic Belt” (Grant Number: X2026106020112) supported by Guangxi Normal University’s Provincial Training Program of Innovation and Entrepreneurship for Undergraduates.

CONFLICT OF INTEREST

The authors declare no conflicts of interest relevant to this study.

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