Proceedings of EKONBIZ 2026
ISBN: 978-99955-45-52-9
UDK: 007.52:368.2.026.4

Submitted: 15.04.2026.
Accepted: 22.05.2026.
Original Article

HOW ARTIFICIAL INTELLIGENCE AFFECTS THE EXPORT TECHNOLOGICAL COMPLEXITY OF MANUFACTURING ENTERPRISES

Hailan Pan
School of Economics & Management, Shanghai Polytechnic University, China
panhailan@sspu.edu.cn
ORCID: 0000-0003-0158-8996

Xueting Zhang
School of Economics & Management, Shanghai Polytechnic University, China
1170709113@qq.com
ORCID: 0009-0002-9890-2071

Abstract: *This study examines the annual reports of A-share-listed manufacturing companies from 2014 to 2023. Using machine learning and text analysis, it constructs firm-level indicators of AI application and assesses their effect on export technological complexity. The results show that AI significantly boosts firms' export technological complexity. AI also empowers export competitiveness through three pathways: improving total factor productivity, optimizing the human capital structure, and stimulating technological innovation. Threshold effect analysis reveals that the impact of AI is not linear. It is significantly constrained by firms' internal resource endowments. Only when the quality of human capital exceeds a certain threshold, and total factor productivity rises to a high level, does AI's enabling effect shift from weak to strong, or even from negative to positive. Heterogeneity research reveals that the effect is larger in eastern regions, among non-state-owned firms, and in places with strong intellectual property protection. These findings offer important insights into employing "AI+" to support high-quality development in the manufacturing sector.*

Key words*: Artificial Intelligence , Export Technological Complexity, Manufacturing,Total Factor Productivity, Technological Innovation*

JEL classification*: O33, F14, L60*

1. INTRODUCTION

As digital economies evolve, cutting-edge technologies like artificial intelligence are redefining global production networks, leveraging the profound convergence of computing capabilities and algorithmic intelligence. Major global economies all view artificial intelligence as a strategic high ground: in 2025, the United States signed and released *Winning the AI Race: America's AI Action Plan*, and the European Commission issued the AI Continent Action Plan, both of which demonstrate that "AI" has become a new benchmark for measuring the comprehensive national strength of major powers. In recent years, China has also introduced a series of policies, such as the Opinions on *Deepening the Implementation of the 'AI+' Initiative*, intended to capitalise on the opportunities presented by the latest technological revolution and foster high-quality economic growth. Beyond driving productivity, the technological upgrading of the secondary sector—the economy's vital core—largely dictates national competitiveness in global trade. In an era of geopolitical uncertainty, understanding how AI empowers firms to refine their export technical standards is crucial. This study explores AI's role in elevating the technical intricacy of enterprise exports, offering suggestions for modernizing manufacturing industries.

2. LITERATURE REVIEW

The technological complexity of China's manufacturing exports is profoundly driven by artificial intelligence, and research consistently demonstrates that AI has a substantial positive impact on this indicator.

From a macro-industry and regional perspective, the impact of AI is amplified through external environmental factors and systemic effects. Research indicates that well-developed digital infrastructure and a strong human capital base provide fertile ground for AI technology spillovers (Yang and Li, 2024). However, another study demonstrate at the industry level that the intensity of AI application generates significant spillover and resource reallocation effects, thereby raising the average export technology complexity of the entire industry (Lin et al., 2024). Nevertheless, this impact does not follow a simple linear relationship. A study identified a nonlinear pattern of diminishing marginal returns in the promotional effect (Xu et al., 2022), while another observed a dynamic “inverted U-shaped” effect(Lin et al., 2024).

At the micro-firm level, the impact of AI is primarily manifested in internal process reengineering and capability enhancement. Research indicates that AI empowers R&D activities and production process innovation through technological innovation effects, directly enhancing firms’ export technology complexity (Zhao and Chu, 2024). Another research found that AI exerts a positive reinforcing effect on the technological complexity of manufacturing firms’ exports by promoting innovation and optimizing the allocation of production factors (Zhang et al., 2023). Furthermore,drawing on resource orchestration theory, found that AI facilitates the upgrading of manufacturing firms by enhancing the use of data as a production factor and improving the quality of internal controls(Xie et al.,2025).

3. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

3.1. THE DIRECT IMPACT OF ARTIFICIAL INTELLIGENCE ON THE TECHNOLOGICAL COMPLEXITY OF EXPORTS

AI redefines production via information optimization and precision engineering. It reduces the costs of navigating international barriers and market demands, fostering a deep alignment with high-value segments (Peng and Yang, 2025). Simultaneously, intelligent automation and digital lines enhance product consistency and precision (Ma et al., 2026). These improvements empower firms to pivot from basic assembly to high-stability, sophisticated exports, thereby increasing their technical complexity. This study hypothesizes:

H1: The application of artificial intelligence can significantly enhance the technological complexity of exports for manufacturing enterprises.

3.2. MEDIATING MECHANISMS THROUGH WHICH ARTIFICIAL INTELLIGENCE INFLUENCES THE TECHNOLOGICAL COMPLEXITY OF EXPORTS

(1) Heterogeneous firm trade theory suggests that productivity is vital for entering technology-intensive export markets. By streamlining production and improving equipment utilization, AI reduces waste and fosters lean management (Liu, 2025). This bolstered productivity provides the financial latitude and risk-bearing strength required to sustain R&D investments for complex product innovation. This study hypothesizes:

H2a: The technological complexity of exports is enhanced by artificial intelligence through the enhancement of total factor productivity.

(2) Aligned with the 'skill-biased technological progress' framework, AI replaces repetitive tasks with a need for multi-skilled technical personnel (Xu and He, 2025). To leverage these tools, enterprises shift their workforce composition toward more educated staff. This human capital optimization facilitates the adoption of sophisticated international technologies and superior manufacturing standards, thereby elevating the technical complexity of exported goods. This study hypothesizes:

H2b: By optimising the human capital structure, artificial intelligence raises the technological complexity of exports.

(3) Beyond its role in production, AI accelerates R&D cycles by analyzing massive patent datasets and utilizing machine learning simulations. Since invention patents reflect greater technical depth than other types (Xu et al., 2023), increased patent output signals a robust core competitiveness. This heightened innovation capacity allows firms to command higher technological premiums globally, facilitating a strategic shift toward the high-value segments of the export chain.This study hypothesizes:

H2c: Artificial intelligence enhances firms’ technological innovation capabilities, thereby increasing the technological complexity of exports.

3.3. THE THRESHOLD EFFECT OF ARTIFICIAL INTELLIGENCE ON EXPORT TECHNOLOGY COMPLEXITY

As a high-tech production factor, the effectiveness of artificial intelligence depends on complementary assets. According to the theory of appropriate technology, if a firm lacks sufficient human capital or suffers from low production efficiency, this may lead to technological mismatches or even result in excess costs due to high investments in intelligent technologies (Yu,2008). Only when the quality of human capital and total factor productivity cross a “tipping point” can enterprises effectively absorb and transform the technological dividends of AI.This study hypothesizes:

H3: The effect of AI on enhancing the technological complexity of manufacturing exports exhibits a threshold effect based on the quality of human capital and total factor productivity.

4. RESEARCH DESIGN

4.1. SELECTION OF VARIABLES

(1) Dependent Variable: Enterprise Export Technology Intensity (ETI)

Enterprise Export Technology Intensity refers to the overall level of technological intensity and relative position within the global value chain as reflected by the value and structural characteristics of an enterprise’s export product portfolio. It reveals an enterprise’s ability to create high-value-added products. Drawing on the research approach of Hausmann et al.(2007), this study first estimates export technology intensity at the industry level:

$$EXPY_j=\Sigma_c \frac{x_{cj}/x_c}{\Sigma_c x_{cj}/x_c} pcgdp_c \#(1)$$

Here, $EXPY_j$represents the export technology complexity of industry j, x_{cj}represents the export value of industry j in region c,$x_c$represents the total export value of region c, and $pcgdp_c$represents the per capita GDP level of region c. To account for heterogeneity at the firm level, we construct a firm-level export technology complexity index by adopting the methodology proposed by Yu and Yu (2018). This paper uses the firm-level total factor productivity (TFP) estimated via the LP method to adjust the EXPY indicator and calculate the firm-level export technology complexity:

$$ETI_i=\frac{TFP_i}{TFP_j} EXPY_{cj}\#(2)$$

Here, TFPi and TFPj represent the average total factor productivity of firm i and industry j, respectively.

(2) Core explanatory variable: Level of AI application (AI)

According to Zhou et al.(2024), This study constructs an AI lexicon from three sources: First, based on the lexicon developed by Yao et al.(2024). Second, 26 AI policy documents were obtained from the Beida Law Database, supplemented by 31 authoritative reports. After word segmentation, frequency screening, and manual removal of irrelevant terms, 47 word pairs were identified. Third, based on the *Classification System for Key Digital Technology Patents (2023)* and high-frequency terms from core literature, the seed terms “Artificial Intelligence” “Machine Learning” “natural language processing” “computer vision” and “virtual reality” were selected. Using the Word2Vec model (Skip-Gram), we trained the model on text from listed companies’ annual reports, extracted the top 40 most similar phrases, and manually removed irrelevant items. Finally, after merging and deduplicating the results, we obtained 121 AI keywords.

(3) Mediating Variables

To explore the underlying mechanisms, we utilize the following transmission variables: Technological Innovation (TI), measured by the logarithm of authorized patents incremented by one; Human Capital (HCS), measured as the ratio of staff with bachelor’s degrees or above; and Total Factor Productivity (TFP_OP), calculated following the OP approach.

(4) Control Variables

Drawing upon existing literature, this research incorporates several covariates to ensure robust results. Firm Size (Size) is proxied by the log-transformed employee count (incremented by one) to capture potential economies of scale. Similarly, Firm Age (Age) is measured as the natural logarithm of one plus the years since establishment, accounting for organizational experience and inertia. R&D Expenditures (RD) is calculated as the ratio of R&D expenditures to total assets, indicating the firm's capacity for technological innovation and absorption; and executive international background (IB) is set as a dummy variable to account for the influence of executives' global perspective on corporate strategy. We also adjust for return on assets (ROA), the Herfindahl-Hirschman Index (HHI), which gauges industry concentration, and the Lerner Index (Lena), which represents market dominance, to account for the influence of financial and market structural elements.

4.2. MODEL SPECIFICATION

To preliminarily examine the impact of artificial intelligence on the technological complexity of firm exports, this study constructs the following two-way fixed-effects model:

$$ETI_{it}=\alpha_0+\beta AI_{it}+\gamma Controls_{it}+\mu_i+\lambda_t+\varepsilon_{it}\#(3)$$

Where ETI_{it} represents the export technology intensity of firm i in year t, AI_{it} represents its level of artificial intelligence, $Controls_{it}$ denotes the set of control variables, and μ_i and λ_t represent firm-specific and year-specific fixed effects, respectively.

To verify the potential transmission channels through which artificial intelligence affects export technology intensity, this study adopts the mediation effect testing framework proposed by Jiang(2022) the following mediation model, where M_{it} represents the mediating variable.

$$M_{it}=\alpha_1+\beta_1 AI_{it}+\gamma_1 Controls_{it}+\mu_i+\lambda_t+\varepsilon_{it}\#(4)$$

$$ETI_{it}=\alpha_2+\beta_2 AI_{it}+\delta M_{it}+\gamma_2 Controls_{it}+\mu_i+\lambda_t+\varepsilon_{it}\#(5)$$

4.3. DATA SOURCES

This study uses A-share listed manufacturing companies from 2014 to 2023 as the initial sample. The baseline data on export technology complexity were sourced from the CEPII-BACI and World Bank's WDI databases, while firm-level data were sourced from the CSMAR database. Sample Selection: Companies with continuous export records were selected, while those who were delisted, ST, or *ST were not included. Observations with missing core indicators were also removed, resulting in a final sample of 12,900 observations.

5. EMPIRICAL ANALYSIS

5.1. BASELINE REGRESSION ANALYSIS

The baseline regression results are shown in Table 1. Column (1) does not account for fixed effects and just contains the primary explanatory variables. All control variables are included in Column (2); year and company fixed effects are successively included in Columns (3) and (4). The primary explanatory variables have significantly positive coefficients in each of the four columns. The regression coefficient for artificial intelligence is 0.0226 and significant at the 1% level, according to the data in Column (4), supporting Hypothesis H1.

Table 1. Benchmark Regression Results

	(1)	(2)	(3)	(4)
AI	0.1725***	0.0577***	0.0516***	0.0226***
	(7.54)	(4.17)	(3.60)	(2.77)
Controls	NO	YES	YES	YES
Firm FE	NO	NO	NO	YES
Year FE	NO	NO	YES	YES
_cons	10.3109***	3.8194***	4.0770***	4.9923***
	(303.87)	(17.47)	(15.80)	(10.32)
N	12900	12900	12900	12900
r2_a	0.0324	0.5631	0.5653	0.4478

Source: *Stata17.*

5.2. BASELINE REGRESSION ANALYSIS

(1) Lagged Variable Method

To ensure the robustness of the conclusions, this study incorporates one-period and two-period lagged variables of AI into the model for re-estimation. The regression results in Table 2 show that the estimated coefficients for both lagged terms are significant within the 1% confidence interval.

Table 2. Lagged Variable Method

	(1)	(2)
	One-period lag	Two-period lag
AI	0.0164*	0.0202**
	(1.96)	(2.19)
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
_cons	4.6528***	4.6029***
	(7.73)	(6.00)
N	11610	10320
r2_a	0.3284	0.2258

Source: *Stata17.*

***, ** and * indicate that the parameter estimates are significant at the 1%, 5%, and 10% significance levels, respectively; the figures in parentheses are cluster-adjusted robust standard errors; the same applies to the table below.

(2) Instrumental Variables

To mitigate potential endogeneity bias, this study develops two categories of instrumental factors to alleviate any endogeneity bias.Initially, in accordance with the methodology of Xiao et al.(2022) we select the mean value of AI applications among other firms in the same industry and year as an instrumental variable (IV_1); we designate the average value of AI applications among peer enterprises within the same industry and year as an instrumental variable (IV_1); Secondly, utilising the study methodology of Xie et al.(2025), we formulate "the cube of the disparity between the mean elevation of prefecture-level cities and the mean AI application score categorised by industry and province" as an instrumental variable (IV_2). Table 3 displays the results of the two-stage instrumental variable regression. In the initial phase, the instrumental variable coefficients above the 1% significance threshold, so excluding the possibility of weak instruments; in the subsequent phase, the AI coefficient continually exhibited a positive and significant value. After accounting for endogeneity, the baseline conclusions remain robust.

Table 3. Instrumental Variables Method

Variable	Tool Variable 1		Tool Variable 2	
	Phase 1	Phase 2	Phase 1	Phase 2
AI		0.0779**		0.0225**
		(2.0825)		(2.1078)
IV_1 / IV_2	0.4077***		0.0012***	
	(11.4651)		(31.4521)	
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	12,898	12,898	12,900	12,900
R-squared	0.783	0.319	0.830	0.325
Cragg-Donald Wald F	226.294[16.38]		3513.473[16.38]	
Anderson canon. corr. LM statistic	P=0.0000		P=0.0000	

Source: *Stata17.*

The Anderson-Canon and LM statistics are tests of instrument identifiability; the Cragg-Donald Wald F statistic is a test for weak instruments; the values in [] correspond to the 10% significance level in Stock and Yogo.

(3) Heckman Two-Stage Method

To mitigate sample selection bias, the initial stage employs the previously mentioned IV_2 as an exclusion variable to compute the inverse Mills ratio (IMR).

In the subsequent phase, the IMR is integrated into the baseline model.

The findings indicate that the regression coefficient for AI is 0.0203 and is significant at the 1% level, confirming that the conclusion holds after accounting for sample selection bias.

Table 4. Heckman Two-Stage Method

Variable	(1)	(2)
AI		0.0203**
		(2.3522)
IMR		0.0262
		(0.0460)
IV_2	-0.0001**	
	(-2.0646)	
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
Observations	12,900	6,753
R-squared		0.937

Source: *Stata17.*

5.3. ROBUSTNESS ANALYSIS

(1) Substituting the Core Explanatory Variable

Given that the measurement method of the explanatory variable may influence the results, we adopted the approach proposed by Zhou et al.(2024) and referred to the Classification System for Key Digital Technology Patents (2023) to match corporate patents with the "Artificial Intelligence" technology code, thereby obtaining the number of corporate AI patents (AI Patent). As shown in Table 6, Column (1), the coefficient is 0.0258 ($p < 0.01$), indicating that the conclusion is robust.

(2) Adding Control Variables

While the baseline regression accounts for firm-specific micro-level features, the macroeconomic conditions of the firm's region may potentially distort the results. This analysis incorporates city-level GDP growth rate (lngdp) and industrial structure (psi) as control variables to address this issue. The results in Table 6, Column (2) indicate that, after accounting for regional macroeconomic swings, the sign and significant level of the primary explanatory variable AI remain mostly consistent, demonstrating the stability of the findings.

(3) Excluding Outliers

To eliminate the influence of outliers on the results, this study employed three methods of testing: First, considering the massive external shocks caused by the 2020 global public health crisis on international trade and corporate production, all observations from 2020 were excluded and the regression was rerun; Second, given the unique characteristics of first-tier cities such as Beijing, Shanghai, Guangzhou, and Shenzhen in terms of digitalization levels and trade environments, the samples from these four cities were excluded and the regression was rerun; Third, industries with inherently high technological content, such as the computer, communications, and other electronic equipment manufacturing sectors, were excluded. Table 5, columns (3)–(5), displays the outcomes. Artificial intelligence's application is still showing a strong beneficial impact, suggesting that AI's contribution to raising the technological complexity of China's manufacturing exports is not limited to a small number of high-tech industries or high-level locations.

Table 5. Excluding Outliers

	(1)	(2)	(3)	(4)	(5)
AI		0.0213***	0.0233***	0.0155*	0.0199**
		(2.65)	(2.84)	(1.67)	(2.45)
AI Patent	0.0258***				
	(3.04)				
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	12900	12900	11610	10250	11176
r2_a	0.4480	0.4477	0.4547	0.4635	0.4183

Source: *Stata17.*

5.4. ANALYSIS OF MEDIATING EFFECTS

(1) Total Factor Productivity

Table 6's column (1) displays the regression coefficient for AI, which is 0.0197 and significant at the 1% level (t=7.35). This suggests that the use of AI considerably boosts corporate productivity gains and raises the technological complexity of corporate exports. Hypothesis H2a is validated.

(2) Human Capital Structure

In Table 6, the estimated AI coefficient for human capital structure is 0.0081 (Column 2), attaining statistical significance at the $p < 0.01$ level (t=4.67). These findings support H2b, suggesting that AI's skill-biased nature drives the advancement of technical complexity in corporate exports.

(3) Technological Innovation

As reported in Table 6, Column (3), the estimated effect of AI on technological innovation is as high as 0.1079 (t=7.86, $p < 0.01$). This confirms Hypothesis H2c, demonstrating that AI promotes technological breakthroughs to increase the export technical intricacy of enterprises.

Table 6. Mediating effect

	(1)	(2)	(3)
AI	0.0197***	0.0081***	0.1079***
	(2.83)	(3.98)	(7.86)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
_cons	4.3759***	0.5372***	0.0028
	(10.74)	(6.58)	(0.00)
N	12900	12900	12900
r2_a	0.4821	0.1389	0.1250

Source: *Stata17.*

5.5. HETEROGENEITY ANALYSIS

(1) Regional Location Heterogeneity

This study categorizes the sample by enterprises' registered locations: Eastern Region and Central, Western, and Northeastern Regions. Table 7 presents regression results. The AI regression coefficient for the Eastern Region is 0.0302 and significant at the 1% level; in contrast, results for the other regions are not significant. This may be due to the Eastern Region's advanced digital infrastructure and greater high-end talent, enabling stronger industrial synergies with AI technology. Additionally, its mature foreign trade environment provides enterprises with greater incentive to use AI to meet international market standards, thereby increasing the sophistication level of exports.

Table 7. Regional Location Heterogeneity

	(1)	(2)	(3)	(4)
	Eastern	Central	Western	Northeastern
AI	0.0302***	0.0175	0.0077	-0.0367
	(3.14)	(0.91)	(0.29)	(-0.92)
Controls	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	4.3748***	6.2547***	6.4524***	5.9411*
	(7.61)	(5.30)	(4.53)	(1.93)
N	8440	2110	1770	580
r2_a	0.4574	0.4273	0.4555	0.4984

Source: *Stata17.*

(2) Heterogeneity in Ownership Structure

Based on their ownership structure, businesses are categorised in this article as either state-owned or non-state-owned. AI has a large favourable impact on non-state-owned businesses but not on state-owned businesses.

The economic justification is that non-state-owned businesses, especially private ones, have a higher motivation to pursue change since they are subject to more intense market rivalry and survival constraints. Consequently, they exhibit greater flexibility in decision-making when applying AI to optimize production processes and drive product innovation.

In contrast, although state-owned enterprises possess financial advantages, they may encounter institutional inertia—such as lengthy decision-making chains and low risk tolerance—during technological transformation. This prevents the full realization of efficiency gains from AI-enabled innovation in the short term.

(3) Heterogeneity in the Strength of Intellectual Property Protection

Based on the median level of intellectual property protection in each location, this study separates the sample into a "high intellectual property protection group" and a "low intellectual property protection group" using the evaluation index created by Fan Gang.

The results of the regression show that AI has a greater driving influence on the technological complexity of company exports in areas with higher levels of intellectual property protection.

In regions with strong IP protection, high-complexity products developed through AI R&D and their core patents receive effective protection, thereby safeguarding firms' innovation returns and incentivizing them to continuously increase investment in intelligent technologies.

Conversely, in regions with weaker protection, innovative achievements face the risk of low-cost imitation, which dampens the motivation to advance AI-enabled technologies.

Table 8. Heterogeneity Analysis

	(1)	(2)	(3)	(4)
	State-owned	Non-state-owned	High intellectual property	Low intellectual property
AI	0.0144	0.0266***	0.0292***	0.0123
	(0.92)	(2.86)	(2.63)	(1.11)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
_cons	4.2087***	5.1505***	4.6059***	5.5468***
	(4.27)	(9.04)	(7.53)	(6.86)
N	4430	8470	6707	6193
r2_a	0.4309	0.4652	0.4554	0.4435

Source: *Stata17.*

5.6. THRESHOLD MECHANISM TEST

A panel threshold modeling technique is employed here to capture the non-proportional dynamics of AI's impact. Here, q_{it} is the threshold variable, and θ is the threshold value to be estimated.

$$ETI_{it}=\alpha_3+\beta_3 AI_{it}\square I(q_{it}\leq\theta)+\beta_4 AI_{it}\square I(q_{it}>\theta)+\gamma_3 Controls_{it}+\mu_i+\lambda_t+\varepsilon_{it} \#(6)$$

The F-statistic for the Human Capital (HCS) single-threshold effect estimation is 51.4***, suggesting statistical significance and rejecting the linear connection hypothesis at the 1% level; HCS does not show a double threshold in the double-threshold test; the F-statistic is 14.75 with a p-value of 0.1900, failing the significance test. The single threshold value for HCS is 0.4152, with a 95% confidence interval of [0.3889, 0.4258], as indicated in Table 10. Consequently, the subsequent analysis step employs single-threshold regression. With an F-statistic of 221.05***, the double-threshold test for TFP is highly significant ($p < 0.01$). However, the triple-threshold result ($F = 123.74$) is statistically negligible, indicating the absence of a triple-threshold effect. Table 10 and Figure 2 display the confidence intervals for the first and second threshold values, which are 8.6016 and 9.7412, respectively. Consequently, the subsequent stage of the study employs two-threshold regression.

Table 9. Results of the Threshold Effect Test

	Threshold Level	F-value	P-value	Significance Level		
				1%	5%	10%
HCS	Single threshold	51.4***	0.0033	31.8346	24.8985	20.2998
	Double threshold	14.75	0.1900	29.8570	23.8046	18.1375
Tfp_op	Single threshold	462.75***	0.0000	32.1763	25.7971	21.2699
	Double threshold	221.05***	0.0000	31.0202	25.1896	21.1896
	Triple threshold	123.74	0.4067	286.405	234.3487	172.8249

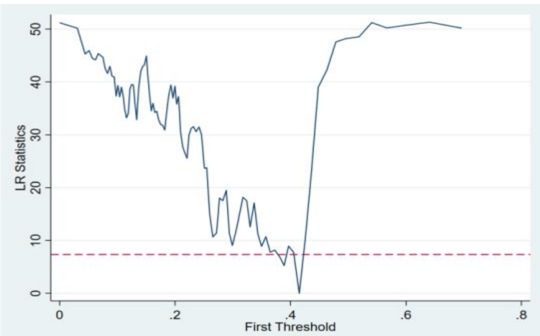
Source: *Stata17.*

Table 10. Threshold Estimates and Confidence Intervals

	Threshold Level	Estimate	95% confidence interval
HCS	Single threshold	0.4152	[0.3889,0.4258]
Tfp_op	Single threshold	8.6016	[8.5732,8.6278]
	Double threshold	9.7412	[9.6899,9.7688]

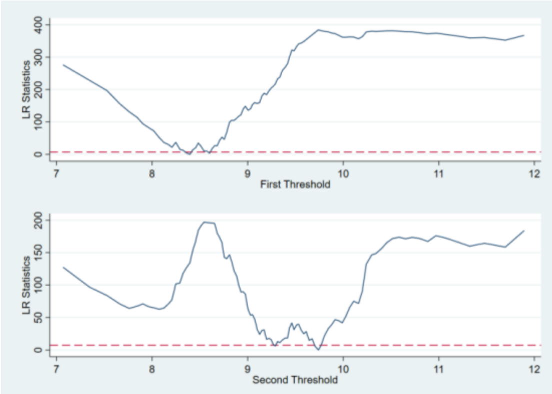
Source: *Stata17.*

Picture 1. Estimated human capital thresholds and confidence intervals



Source: *Stata17.*

Picture 2. Estimated total factor productivity thresholds and confidence interval



Source: *Stata17.*

Table 11 presents the results of a single-threshold regression using human capital quality as the threshold variable and a double-threshold regression using total factor productivity as the threshold variable. When the quality of human capital is below 0.4152, the impact on AI is not significant. However, as the quality of human capital continues to rise and crosses the threshold, the estimated coefficient for AI becomes significantly positive at the 1% level. This indicates that only high-quality human capital can effectively align with intelligent production, thereby increasing productivity and ultimately enhancing the technological complexity of exports. Conversely, low-quality human capital hinders the positive impact of AI on the technological complexity of China's manufacturing exports, suggesting that AI's influence on the technological complexity of China’s manufacturing exports exhibits a threshold effect related to human capital quality.

When total factor productivity is below the threshold of 8.6016, AI exerts a markedly adverse influence, suggesting that insufficient productivity bottlenecks AI’s ability to enhance export technological sophistication.

Once TFP crosses the single threshold and enters the second interval, the impact of AI turns positive but fails to pass the significance test. This suggests that, at this stage, enterprises’ technological absorption capacity and resource allocation efficiency have not yet fully aligned with the implementation requirements of AI, and the enabling effects have not yet been fully realized. When TFP exceeds the 9.7412 dual barrier, AI begins to drive the technical intricacy of exports with 1% statistical significance during the third period. This suggests that AI's impact on exports' technological complexity only becomes noticeable when TFP hits a particular threshold. To sum up, H3 has been verified.

Table 11. Threshold Effect Test

Threshold Variable	(1)	(2)
	HCS	Tfp_op
AI (HCS ≤ 0.4152)	0.0118	
	(1.45)	
AI (HCS > 0.4152)	0.0632***	
	(3.82)	
AI (Tfp_op ≤ 8.6016)		-0.1390***
		(-9.55)
AI (8.6016 < Tfp_op ≤ 9.7412)		0.0094
		(1.02)
AI (Tfp_op > 9.7412)		0.0168***
		(9.16)
control variable	control	control
Observations	12990	12990
R-squared	0.5304	0.5585

Source: *Stata17.*

CONCLUSION

Based on an empirical analysis of listed manufacturing companies from 2014 to 2023, this study draws the following conclusions: First, the application of artificial intelligence significantly increases the technological complexity of firms' exports; second, total factor productivity, human capital structure, and technological innovation are the core mediating pathways through which AI exerts its enabling effects; third, The realisation of AI dividends is limited by regional, ownership, and institutional considerations, with more pronounced benefits in eastern regions, non-state-owned firms, and areas with robust intellectual property protection; fourth, the impact of AI exhibits significant threshold characteristics, with its enabling effects showing nonlinear growth once human capital and total factor productivity cross specific critical thresholds.

Based on the above, this paper proposes three suggestions:

First, increase investment in AI infrastructure to narrow the "digital divide" between regions. Results show that AI makes the technology complexity of exports much higher, but analysis of different areas shows that this gain is bigger in the eastern regions with good digital infrastructure, but it is not big in the central, western, and northeastern regions. So the government should work on building new infrastructure like computing centers and industrial internet, and focus on giving policy help to central, western, and northeastern regions to lower the first costs and information problems for companies in these areas to use AI technology. By using focused industry help, the government should help manufacturing in central and western regions get out of the low-value trap and use AI to make a big change in production methods.

Second, use AI as the main engine, and then drive export growth through different ways like productivity, worker skills, and tech advances. Test results show that AI raises export technology by using resources better to raise productivity, and changes worker skills toward more skilled workers, and speeds up getting new patents. Because the limit effect of worker skills is 0.4152, the government should improve job training and college education, and focus on training people with many skills for smart production. And companies should also do worker training when they bring in AI equipment, so that the skill level matches new technology.

Third, we must always make better the rules and the patent protection system, and then help all kinds of companies do smart changes. Results show that AI helps more in non-state-owned companies and in places with better patent protection. On one hand, we should lower barriers to financing and technology access for the non-public sector. This addresses the competitive pressures it faces. At the same time, we need to deepen institutional reforms in state-owned enterprises and optimize decision-making chains. These changes will make them more flexible in applying intelligent technologies. On the other hand, we must strengthen protection for core algorithms and invention patents in the AI sector. Only within a high-standard legal framework can enterprises ensure their innovative returns are protected from low-cost imitation. This will incentivize them to invest more in intelligent technologies and drive the manufacturing sector toward high-quality transformation.

REFERENCES

[1] Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of economic growth*, 12(1), 1-25.

[2] Jiang, T. (2022). Mediating effects and moderating effects in causal inference. *China Industrial Economics*, 5(5), 100-120.

[3] Lin, C., Xiao, S., & Tang, P. (2024). Does artificial intelligence improve export technical complexity upgrade of manufacturing enterprises? Evidence from

China. *Sage Open*, 14(3), 21582440241267126.

[4] Liu, X. (2025).Advantages and technical analysis of automatic control for coal mine electromechanical equipment. *China Coal*, 51(S1), 431-436.

[5] Ma, D., Zhu, Y. & Pan, B. (2026).Research on the Intelligent Transformation of Industrial Automation Production Lines Based on Intelligent Manufacturing Technology.*Value Engineering*, 45(01), 29-32.

[6] Peng, Y. & Yang, B.(2025). Artificial Intelligence and International Trade: Global Enabling Digital Trade Index Analysis Report2024. *World Economy Studies*, (10), 3-14+135.

[7] Xiao, T., Sun, R., Yuan, C. & Sun, J.(2022). Corporate Digital Transformation, Restructuring of Human Capital, and the Share of Labor Income. *Journal of Management World*, 38(12), 220-237.

[8] Xie, W., Lin, M., Zheng, D., Qin, L. & Yu, J. (2025). How Does Artificial Intelligence Technology Drive the Transformation and Upgrading of Manufacturing Enterprises? — Based on the Chain-like Mediating Role of Data Elements and Internal Controls. *Journal of Technology Economic*s, 44(04), 72-88.

[9] Xie, W., Lin, M., Zheng, D., Qin, L. & Yu, J.(2025). What Mechanisms Does Artificial Intelligence Technology Employ to Foster the Transformation and Upgrading of Manufacturing Firms: A Chain-mediated Role of Data Element and Internal Control. *Journal of Technology Economics*, 44(04), 72-88.

[10] Xu, X., Zhao, M., Li, T. & Li, S. (2023). Data Factor and Enterprise Innovation: The Perspective of R&D Competition. *Economic Research Journa*l, 58(02), 39-56.

[11] Xu, Y. & He, H.(2025). The Impact of "AI Plus" on Employment and Relevant Countermeasures. *Education and Vocation*, (13), 97-104.

[12] Xu, Y., Zhu, J., & Tao, C. (2022). Intelligent Manufacturing, Labor Skill Structure and Export Technology Complexity. *Finance and Trade Research*, 33(03), 16-27.

[13] Yu, D.(2008). A Review of Theoretical Research on Appropriate Technology. *Research on Financial and Economic Issues*, (02), 22-28.

[14] Yu, J. & Yu, D. (2018). Government Subsidies, Industrial Competition and Enterprises' Export Technology Complexity. *Journal of Finance and Economics*, 44(03), 112-124.

[15] Yao, J., Zhang, K., Guo, L. & Feng, X. (2024). How Does Artificial Intelligence Boost Corporate Productivity? — A Perspective Based on Labor Force Skill Structure Adjustments. *Journal of Management World*, 40(02), 101-116+133+117-122.

[16] Yang, X. & Li, H. (2024). The Impact of Artificial Intelligence on the Technological Sophistication of China's Manufacturing Industry Exports: An Empirical Test of Industrial Robot Applications. *Research on Development*, (06), 67-78.

[17] Zhang, B., Chen, J., Zhu, J. & Yan, Z.(2023). Artificial Intelligence and Increased Technological Complexity of Enterprise Exports. *Journal of International Trade*, (08), 143-157.

[18] Zhao, C. & Chu, T. (2024). Study on the Influence of Artificial Intelligence Application on the Technical Complexity of Export——Based on Chinese Industry Panel Data. *Forum on Science and Technology in China*, (06), 58-66.

[19] Zhou, P., Wang, Z., Tan, C. & Song, M.(2024). The Value of Digital Technology Innovation:From the M&A Perspective and Machine Learning Methods. *China Industrial Economics*, (02), 137-154.

[20] Zhou, K., Qu, Z., Shi, Y. & Gao, D.(2024). Local Government Debt Governance and New Quality Productive Forces in Private Enterprises:A Perspective on Key Digital Technological Breakthrough. *Economic Review*, (04), 20-37