How Artificial Intelligence Is Driving the Upgrading of the Global Manufacturing Value Chain?

Huawei Wang*

Changsha University of Science & Technology, Changsha City, 410076, China

huaweiwang_2005@outlook.com

Abstract. Based on panel data from Chinese A-share listed manufacturing companies from 2012 to 2022, this study empirically examines the impact of artificial intelligence (AI) levels on the technological complexity of manufacturing exports. The findings reveal a significant positive correlation between AI levels and the technological complexity of manufacturing exports, indicating a "synergistic" relationship. Artificial intelligence can indirectly enhance the technological complexity of manufacturing exports by improving resource allocation efficiency and reducing institutional transaction costs. This study effectively elucidates the role of artificial intelligence in enhancing the technological complexity of manufacturing exports, providing reliable policy guidance for achieving high-quality manufacturing exports and upgrading the global value chain.

Keywords: Artificial Intelligence, Global Value Chains, Export Technology Complexity.

1 Introduction

Manufacturing serves as the bedrock of economic development. Since 2010, China's total manufacturing output has ranked first globally for 15 consecutive years, with value-added reaching 8 trillion yuan in 2024 and contributing more than 30% to global manufacturing growth. However, within the global value chain, China's manufacturing sector still faces challenges such as reliance on foreign key technologies and an excessive proportion of low-end segments, posing a risk of "low-end lock-in." There is an urgent need to transition toward high-end and intelligent manufacturing. At the same time, as global trade uncertainties intensify, the traditional low-cost competition model is becoming unsustainable, and the technological complexity of export products has become a core factor in measuring a company's international competitiveness. Governments worldwide are generally increasing investment in artificial intelligence research and development to promote its deep integration with the real economy.

As a core technology of the Fourth Industrial Revolution, artificial intelligence can significantly improve production efficiency and reduce operating costs, while helping enterprises compete globally through intelligent design, accurate forecasting, and automated production. In the export sector, artificial intelligence helps enhance tech-

A. Bhattacharjya et al. (eds.), *Proceedings of the 2026 4th International Conference on Management Innovation and Economy Development (MIED 2026)*, Advances in Economics, Business and Management Research 405,
https://doi.org/10.2991/978-94-6239-787-3_42

nological innovation capabilities, optimize production processes, improve market adaptability, and increase product value-added, thereby providing new momentum for the upgrading of manufacturing exports. In light of this, this paper constructs a fixed-effects model to empirically examine the impact of AI on the technological complexity of manufacturing exports, providing empirical evidence and policy recommendations for breaking free from "low-end lock-in" and advancing the upgrading of the global manufacturing value chain.

Existing research primarily focuses on two dimensions: global value chain upgrading and artificial intelligence. Regarding global value chain upgrading, the Global Value Chain Positioning Index proposed by Koopman et al. is widely used to measure a country's position in the international division of labor [1]; Hausmann et al., on the other hand, emphasize that the technological complexity of exports is a key indicator for measuring value chain positioning [2], as products with high technological complexity help drive the manufacturing sector toward the higher end of the value chain. In the field of artificial intelligence research, Yao Jiaquan et al. employed text analysis to construct an indicator of AI application levels at the firm level [3], while Lü Yue et al. measured the penetration of AI technology from the perspective of smart device imports [4]. Existing research indicates that AI can promote an increase in export technology complexity. Zhang Bingbing et al. found that AI technology can significantly enhance firms' export technology complexity, with its mechanisms including promoting firm innovation and optimizing factor allocation structures [5]. Chen Wen et al. further examined export resilience and found that the application of industrial robots significantly enhances firms' export resilience by increasing productivity and the technological complexity of exported products [6]. These studies provide important empirical evidence for the role of AI in empowering the upgrading of manufacturing exports. However, existing literature largely focuses on the direct effects of AI on export complexity or single mediation pathways, while comprehensive examinations of multiple mechanisms—such as factor allocation efficiency, institutional transaction costs, and government digital governance—remain relatively limited.

In summary, against the dual backdrop of accelerating restructuring of global value chains and the transformation and upgrading of the manufacturing sector, exploring how to transform "breakthroughs in artificial intelligence technology" into opportunities for "advancing China's position in global manufacturing value chains" holds significant strategic importance for breaking free from the "low-end lock-in" dilemma facing China's manufacturing industry. In light of this, this paper constructs a fixed-effects model to empirically examine the impact of artificial intelligence on the technological complexity of manufacturing exports, with the aim of providing empirical evidence and policy recommendations to overcome technological bottlenecks and propel China's transition from a "manufacturing giant" to a "manufacturing powerhouse."

2 Research Hypotheses

2.1 Factor Allocation Efficiency

Through big data, machine learning, and intelligent decision-making systems, artificial intelligence can accurately identify redundancies and shortages in production processes, enabling the dynamic reallocation of the three key factors—capital, labor, and data—across departments and time periods. On the one hand, algorithmic production scheduling and predictive maintenance reduce equipment idling and raw material waste, directly lowering the capital-to-labor ratio per unit of output, allowing enterprises to allocate more resources to the R&D of high-complexity products and brand design; on the other hand, AI-driven supply chain visualization platforms match upstream and downstream production capacity in real time, shortening the "idle time" of highly skilled labor, high-end components, and R&D funds within the industrial chain, thereby increasing the marginal output of factors. As factor allocation efficiency improves, the "resource misallocation tax" faced by enterprises decreases. With the same budget, companies can hire more highly skilled engineers and import higher-quality intermediate goods, thereby significantly increasing the technological complexity of exports. This smooths the upgrade path between factors and products, optimizing the transmission chain between artificial intelligence and the technological complexity of exports. We therefore propose Hypothesis H1:Advances in artificial intelligence positively influence the technological complexity of manufacturing exports by improving factor allocation efficiency.

2.2 Institutional Transaction Costs

Blockchain-based electronic contracts, smart customs clearance, and automated integration with government data reduce the time required for customs clearance, commodity inspection, and compliance, thereby lowering institutional transaction costs. Order response times are shortened, enabling the timely delivery of highly complex, small-batch, and customized products; savings on compliance costs improve cash flow, incentivizing firms to shift toward more technologically advanced, smaller-order, differentiated product lines, thereby reducing lock-in to low-end markets. The diminishing marginal returns on institutional costs reinforce a virtuous cycle involving "artificial intelligence—transaction costs—export complexity." Based on this, we propose Hypothesis H2: Advances in artificial intelligence promote an increase in the technological complexity of exports by reducing institutional transaction costs.

2.3 Government Digital Governance

The "one-stop online service" for digital government integrates customs, tax, foreign exchange, and intellectual property data, enabling instant online approvals and providing institutional interfaces for artificial intelligence. The opening of government data facilitates instant matching of high-end intermediate goods, talent, and financing solutions, reducing the rate of factor misallocation; electronic contracts and smart customs declarations streamline compliance processes. Once the transaction chain is digitized and streamlined, high-complexity orders overcome the barriers to economies of scale, allowing enterprises to redirect R&D, branding, and design resources toward high-value-added product lines. R&D subsidies, talent incentives, and export tax rebates are precisely channeled toward high-complexity projects via "policy algorithms," creating a dual-engine drive of efficient factor mobility and decreasing institutional costs. This amplifies the marginal effect of AI on the technological complexity of exports, achieving synergistic progress between digital governance and AI. This leads to Hypothesis H3: Government digital governance exerts a positive moderating effect on the relationship between artificial intelligence and the technical complexity of manufacturing exports; the higher the level of government digital governance, the stronger the "synergistic advancement" between artificial intelligence and the technical complexity of manufacturing exports.

3 Research Design

3.1 Model Building

To investigate the impact of artificial intelligence on the technological complexity of manufacturing exports, this paper constructs the following basic econometric model:

$$\mathrm{lnEXPY}_{\mathrm{it}} = \alpha_0 + \alpha_1 \mathrm{AI}_{\mathrm{it}} + \alpha_n Controls_{it} + v_i + v_t + \varepsilon_{it} \tag{1}$$

In this model, the subscripts i and t denote the firm and the year, respectively. The dependent variable ln EXPY represents the technical complexity of exports; the independent variable AI represents the level of artificial intelligence; and Controls denotes the set of control variables. α0 is the constant term, α1 andαn are the estimated coefficients, vi and vt are the firm and year fixed effects, andεit is the random error term.

3.2 Variable Selection

Dependent Variable. The dependent variable in this paper is export technology complexity. The estimation process consists of three steps: First, following the approach of Hausmann et al., we calculate export technology complexity at the product level by weighting each country's per capita GDP using the share of that country's exports of a given product in its total exports. Second, product codes are matched with the National Economic Industry Classification to categorize products into various manufacturing sectors, and the export technology complexity of products is aggregated at the industry level to obtain industry-level export technology complexity. Third, the industry-level export technology complexity is adjusted using the ratio of firm-level total factor productivity (calculated via the LP method) to the industry-average total factor productivity, ultimately yielding firm-level export technology complexity.

Key explanatory Variable. In this paper, the independent variable is the level of artificial intelligence. The steps for matching patent numbers by classification code are as follows:(1)Clean the raw patent data to obtain the primary classification code.(2)Based on the "Artificial Intelligence Technology Patent Classification System Table" in the "Key Digital Technology Patent Classification System(2023)"released by the China National Intellectual Property Administration in September 2023,match the primary classification codes to identify AI patents that meet the criteria.(3)Using the AI patent data obtained through the above steps, we compile statistics on patent applications and grants for each province and municipality.(4)We further match the data by the names of companies in which listed companies hold equity stakes to calculate their patent application and grant statistics.

Control Variable. In addition to the level of artificial intelligence, the technological complexity of manufacturing exports is influenced by numerous factors. Based on a review of domestic and international literature, this paper selects control variables at three levels for analysis. At the firm-level, these include: capital intensity(lnklr), long-term debt-to-equity ratio(dlcr), return on equity(roe), industry competition intensity(hhi), and Shareholding Concentration: Largest Shareholder's Ownership Percentage (Top1). The definition, observation quantity, mean value, standard deviation and other descriptive statistical characteristics of all variables in this paper are shown in Table 1.

Table 1. Variable Definition and Descriptive Statistics

Variable	Number of observations	Selection of Indicators	mean	Standard deviation	minimum value	maximum value
Efficiency	21527	Calculated based on input-output indicators using the data envelopment analysis method	0.124	0.270	0	20.965
Regulation	18225	The ratio of the sum of a company's selling, general, and administrative expenses and financial expenses to total assets	0.092	0.073	-0.047	1.079
gov digital	21527	Set the value to 1 if included in the pilot list; otherwise, set it to 0.	0.436	0.496	0	1
lnklr	21527	The logarithm of the ratio of the average annual net value of fixed assets to the average annual number of employees	2.127	1.278	0.481	8.259
dlcr	21527	Ratio of Long-Term Liabilities to Long-Term Capital	0.106	0.121	0	0.543
roe	21527	Ratio of annual profit to operating revenue	0.052	0.873	-72.733	2.313
hhi	21527	Hufford Index	0.061	0.057	0.013	0.495
Top1	21527	Percentage of total shares held by the largest shareholder	33.500	14.311	1.84	89.990

3.3 Data Sources and Processing

This study uses Chinese A-share listed manufacturing companies from 2013 to 2022 as its sample. Data sources include CEPII, Wind, RESSET, the World Bank's WDI database, and the*China Industrial Statistical Yearbook*. RESSET provides data on company employees and educational attainment, while WDI and CEPII provide per capita GDP and trade data, respectively.

To narrow the scope of the study, non-exporting firms with no export revenue during the sample period were excluded. Data processing was also conducted as follows:(1) a small number of missing values were imputed using linear interpolation; (2) ST, ST*, and PT-classified companies were excluded; and (3) data with severe missing values, as well as outliers and extreme values, were removed. The final dataset comprises 21,527 observations, covering 28 manufacturing sectors and 3,181 listed companies.

4 Empirical Results and Analysis

4.1 Regression to the Mean

Table 2 reports the results of benchmark regression, robustness test and endogeneity test. Column (1) only includes the core explanatory variable ln AI without control variables; Column (2) further incorporates all control variables. The results show that the estimated coefficient of the core explanatory variable ln AI is significantly positive at the 5% level or higher in all columns, indicating that an increase in AI levels significantly promotes the increase in the complexity of manufacturing export firms, and that there is a robust positive correlation between the two. In terms of economic significance, taking Column (2) as an example, a 100% increase in AI levels is associated with an approximate 0.77% increase in the complexity of manufacturing export firms.

4.2 Robustness test

To ensure the reliability of the baseline results, this study conducted two types of robustness tests: first, by replacing the measurement method of the core explanatory variable, using an artificial intelligence level index based on word frequency induction to substitute for the number of patents; second, by altering the sample window period, excluding data from 2020–2022—which was disrupted by the public health crisis—and performing the regression analysis again. In both tests, the estimated coefficients of the core explanatory variables were significantly positive at the 5%level or higher, indicating that the baseline conclusions are robust.

4.3 Endogeneity Test

To mitigate endogeneity issues potentially caused by omitted variables and reverse causality, this study employs three strategies: regressing the core explanatory variable with a one-period lag, regressing all variables with a one-period lag, and using the core explanatory variable with a one-period lag as an instrumental variable in a two-stage least squares estimation. Additionally, the policy of the National Pilot Zones for AI Innovation and Application is treated as a quasi-natural experiment, and a multi-period DID model is constructed for testing. All results of the endogeneity treatment indicate that improvements in AI levels still significantly promote increases in the technological complexity of manufacturing exports, further validating the core conclusion.

$$\mathrm{lnEXPY}_{\mathrm{it}} = \alpha_0 + \alpha_1 \mathrm{treat} \times \mathrm{post} + \alpha_{\mathrm{n}} Controls_{it} + v_i + v_t + \varepsilon_{it} \tag{2}$$

Table 2. Benchmark Regression, Robustness Test and Endogeneity Test Results

	Regression to the Mean		Robustness test		Robustness test				
Variable	(1) Two-way fixed-effects *lnEXPY*	(2) Add a control variable *lnEXPY*	(3) Replace the explanatory variable *lnEXPY*	(4) Change the window period *lnEXPY*	(5) Explanatory variable,one period lagged *lnEXPY*	(6) Explanatory variable,one period lagged *lnEXPY*	(7) Phase One *lnAI*	(8) Phase Two *lnEXPY*	(9) Testing of Exogenous Policies *lnEXPY*
lnAI	0.007***	0.008***		0.007***	0.008***	0.007***		0.014***	
	(0.002)	(0.001)		(0.001)	(0.001)	(0.001)		(0.003)	
lnAI_new			0.002**						
			(0.001)						
IV							0.903***		
							(0.074)		
treat×post									0.012***
									(0.004)
Constant	10.707***	10.711***	10.712***	10.731***	10.713***	10.689***	0.012	10.789***	10.712
	(0.002)	(0.009)	(0.009)	(0.007)	(0.010)	(0.005)	(0.016)	(0.0121)	(0.009)
Control variable	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	21527	21527	21527	13126	18168	18167	18168	18168	21527
R^2	0.371	0.411	0.409	0.553	0.399	0.259	0.737	0.195	0.411

Note: ***,**, and*indicate significance at the 1%,5%, and 10%levels, respectively. The figures in parentheses represent robust standard errors at the firm level. All regressions were conducted with firms and time fixed and control variables included; the same applies below.

4.4 Mechanism Verification

Table 3 presents the estimation results of mediating effect and moderating effect. This paper further examines the transmission mechanisms and moderating conditions through which artificial intelligence influences the technological complexity of exports. Regarding the mediating mechanisms, AI significantly enhances factor allocation efficiency(with a coefficient that is significantly positive at the 1%level)and simultaneously significantly reduces institutional transaction costs(with a coefficient that is significantly positive at the 1%level).Combined with existing literature findings that these two types of mediating variables promote increases in export technology complexity, it can be inferred that factor allocation efficiency and institutional transaction costs are two parallel channels through which AI enables export upgrading, confirming Hypotheses H1 and H2.Regarding the moderating mechanism, the coefficient of the interaction term between government digital governance and AI is significantly positive at the 1%level,while the coefficient for digital governance alone is negative. This indicates that a high level of government digital governance amplifies the marginal effects of AI, thereby validating Hypothesis H3.

Table 3. Mediating Effect and Moderating Effect Test Results

Variable	Factor Allocation Efficiency		Institutional transaction costs		Government Digital Governance
	(1)	(2)	(3)	(4)	(5)
	Efficiency	*lnEXPY*	*Regulation*	*lnEXPY*	*lnEXPY*
lnAI	0.002*** (0.001)	0.008*** (0.001)	-0.003*** (0.001)	0.008*** (0.001)	0.003*** (0.002)
Efficiency		0.012*** (0.011)			
Regulation				0.099** (0.047)	
gov digital					-0.005*** (0.005)
interact					0.007*** (0.002)
Control variable	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
N	21527	21527	18226	18226	21527
R^2	0.324	0.411	0.268	0.413	0.417

5 Conclusions and Implications

Based on panel data from Chinese A-share listed manufacturing companies from 2012 to 2022, this paper constructs a two-way fixed-effects model and incorporates mediating and moderating mechanisms to systematically examine the pathways through which artificial intelligence influences the technological complexity of exports. The study finds that artificial intelligence is significantly positively correlated with the technological complexity of manufacturing exports and indirectly boosts export complexity through two parallel channels: improving factor allocation efficiency and reducing institutional transaction costs; Government digital governance significantly amplifies the marginal effects of AI. Based on these findings, policy implications include: leveraging AI's role in factor allocation to foster a new ecosystem of high-quality inputs; advancing the development of digital ports and smart compliance systems with the goal of eliminating institutional transaction costs; and amplifying the export leapfrog effect by prioritizing the upgrading of government digital governance.

References

1. Koopman, R., Wang, Z., & Wei, S.-J. (November 2012). Tracing value-added and double counting in gross exports (NBER Working Paper No. 18579). National Bureau of Economic Research. https://doi.org/10.3386/w18579
2. Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. Journal of Economic Growth, 12(1), 1–25. https://doi.org/10.1007/s10887-006-9009-4
3. Yao, Jiaquan; Zhang, Kunpeng; Guo, Lipeng; & Feng, Xu. (2024). How Does Artificial Intelligence Enhance Corporate Productivity? — A Perspective Based on Labor Skill Structure Adjustment. Management World, 40(02), 101–116, 133, 117–122. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018.
4. Lü Yue, Zhang Haotian, & Gao Kailin. (2024). "Extending and Strengthening China's Industrial Chains in the Age of Artificial Intelligence: Microevidence Based on Manufacturing Firms' Imports of Smart Equipment." China Industrial Economics, (01), 56–74. https://doi.org/10.19581/j.cnki.ciejournal.2024.01.004.
5. Zhang Bingbing, Chen Jing, Zhu Jing, & Yan Zhijun. (2023). Artificial Intelligence and the Enhancement of Technological Complexity in Corporate Exports. International Trade Issues, (08), 143–157. https://doi.org/10.13510/j.cnki.jit.2023.08.005.
6. Chen Wen, Fan Xueqing, & Yao Quanfang. (2026). Industrial Robot Applications and Corporate Export Resilience. Economic Dynamics, (02), 74–100.