Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 15, No. 1, 2024

The Impact of Artificial Intelligence on the Technological Complexity of China's Manufacturing Exports

Sini Zeng, Meihua Wang

Business School, Foshan University, Guangdong Foshan, 528000, China

Abstract: Artificial Intelligence(AI) has become an important means to enhance the technological complexity of manufacturing exports. Based on the theories of comparative advantage, technological innovation, new trade theory, and skill-biased technological progress, this study empirically examines the relationship between AI and the technological complexity of manufacturing exports in 30 provinces(excluding Tibet) from 2012 to 2021. The results indicate that AI has significant positive impact on the technological complexity of manufacturing exports, which is robustly validated, especially in the eastern and central regions. Based on these findings, the paper suggests targeted recommendations.

Keywords: Artificial Intelligence; Export Technical Complexity; Manufacturing Industries.

1. Introduction

According to data released on the Chinese government website, China's value-added of industry above scale grew by 4.6% year-on-year in 2023, and the overall scale of the manufacturing industry has ranked first in the world for 14 consecutive years. However, China's manufacturing sector is still facing challenges such as rising labor costs, tight land resources, and strengthened environmental protection policies, all of which are testing the transformation and upgrading of the manufacturing sector. At the same time, insufficient innovation capacity in high-end manufacturing, increased uncertainty in global trade, coupled with more market access barriers, especially the U.S.-China trade friction, the imposition of technological embargoes and export restrictions on China's hi-tech manufacturing industry, have seriously affected the access of Chinese enterprises to key technologies and components. In order to meet these challenges, China's manufacturing sector must accelerate technological innovation and optimize its industrial export structure in order to achieve sustainable development.

Artificial intelligence, as a universal technology with great potential, has been widely valued globally, and countries have incorporated it into the core areas of national strategies, realizing that AI can inject momentum into the manufacturing industry and promote the structural optimization of the industry as a whole (Kaiming Guo, 2019)[1]. China has ushered in a new opportunity in the digital era, which provides an innovative strategy for export upgrading, and the development of AI is seen as a key way to reach this goal. The release of the New Generation Artificial Intelligence Development Plan (2017) provides a clear direction for the development and strategic positioning of the domestic AI industry, with the goal of leading the global AI industry by 2030. The report of the 20th Party Congress similarly emphasized the importance of AI and advocated the deep integration of AI with the real economy. According to data released by the China Academy of Information and Communication Research, the size of China's AI core industry will reach 578.4 billion yuan in 2023, with a growth rate of 13.9%, and is expected to exceed 600 billion yuan by 2026, showing broad market prospects and the potential to become the world's largest AI market. Therefore, in recent years, academics have widely explored the role and influence mechanism of AI on the complexity of export technology, stimulating the structural optimization of China's manufacturing industry and moving up the value chain, and also providing theoretical references for the governmental departments to introduce corresponding support policies.

From the established research results, the studies related to this paper can be mainly divided into two categories as follows: the first category is the relationship between artificial intelligence and export trade. Studies have shown that AI-enabled manufacturing can enhance a country's export strength by expanding the scale of international trade and improving product quality (Yunhua Tian et al, 2020) [2].Qigang Yuan(2022) et al [3] found that, as a typical application of AI technology, industrial robots significantly improve the quality of enterprises' export products, and in the process of application, enterprises with a large scale and a leading advantage have a higher possibility of improving the level of export products. Empirically,Yue Lv et al (2020)[4] concluded that AI can enhance China's position in the global value chain from the perspective of microenterprises. The second category of literature related to this paper is focused on the relationship between technology and export technological complexity. Xiaojing Qian et al(2020)[5] find that digital infrastructure development helps to increase the technological complexity of export products through the mechanism of technology diffusion. Lin Dang et al (2021) [6] used national panel data to verify that digital transformation significantly improves production effectiveness and market response agility by optimizing business models and organizational structures, enabling the manufacturing industry to flexibly respond to changes in the international market and successfully develop products with high technological content.

Existing scholars' research on the relationship between AI and export technological complexity provides a rich research foundation for this paper, but it mainly focuses on the country and enterprise level, with less research on the province- and industry-specific nature, which is urgently in need of further research expansion. Based on this, the link between AI and export technological complexity is explored through theoretical and empirical analyses, using a sample of 30 Chinese provinces from 2012-2021.

The possible marginal contributions of this paper are: first, exploring the mechanism of AI's effect on export technological complexity with theoretical analysis combined with empirical research enriches the research related to AI and export technological complexity; second, a deeper understanding of how AI affects export technological complexity can help enterprises and the government to formulate a more effective strategy to promote the transformation of traditional industries to high technology and high value-added direction and enhance international competitiveness.

2. Theoretical Analysis and Research Assumptions

The technological complexity of exports reflects a country's technological sophistication and is influenced by the level of technological innovation. From the theory of technological innovation, it is known that innovation is the driving force for sustainable economic development and growth. The cutting-edge technology of artificial intelligence will certainly improve the trade structure to increase the technological content of export products. First of all, it improves the quality and accuracy of manufacturing products. In the production process, automation and robotics are the main areas in which AI is applied, and intelligent robots can increase assembly speed, perform precision operations, as well as replace manual labor in scenarios that require a high degree of accuracy and repetition, reducing human error and defective products, which enables the manufacturing industry to produce higher-quality products (Yaya Li and An Pan , 2017)[7], which in turn contributes to the improvement of export product quality. Second, AI technology improves efficiency by optimizing the production process. Because the application of intelligent robots can realize more efficient production lines and logistics management, it significantly reduces the loss of time and resources in production activities. Finally, AI technology significantly improves product innovation and personalization by deeply analyzing consumer data, predicting market trends, assisting designers in quickly generating and optimizing design solutions, providing personalized recommendations, as well as realizing intelligent manufacturing and supply chain optimization, which not only improves the competitive potential of the products, but also increases the technological complexity of the manufacturing industry's exports (Zhaoliang Ma et al, 2022) [8]. As a result, this paper proposes hypotheses:

Hypothesis H1: The development of artificial intelligence contributes to the upgrading of the technological complexity of manufacturing exports.

3. Research Design and Data Sources

3.1. Benchmark Model

Based on the theoretical analysis in the previous section, it is learned that artificial intelligence can, to a certain extent, have an impact on the export technological complexity of the manufacturing industry, according to which the following econometric model is constructed:

$$expy_{it}=\beta_0+\beta_1 AI_{it}+\beta_2 X_{it}+\delta_{it}+\mu_{it} \quad (1)$$

The technological complexity of manufacturing exports in province i (i=1, 2,..., 30) in year t (t=2012,..., 2021) is denoted by, and the level of AI development in province i in year t is denoted by, are control variables, including economic growth (gdp), R&D innovation (pat), infrastructure (infra), environmental regulation (env), and foreign direct investment (FDI), as fixed effects, and a random disturbance term.

3.2. Variable Selection

1.Explained variable: technical complexity of manufacturing exports

In this paper, we choose to start from the industry and adopt the methodology of Hausman (2007) [9] to measure the export technological complexity, which is done as follows:

First, the export technological complexity is calculated for the industry.

$$\mathrm{PRODY_K}=\sum\frac{\mathrm{x_k/x}}{\sum \mathrm{x_k/x}}\times \mathrm{Y_j} \quad (2)$$

$PRODY_K$ 、 x 、 x_k and Y_j denote the export technical complexity of industry k, China's total exports, China's export value of industry k, and the GDP of province (city) j.

Further, the export technical complexity at the industry level is summed up to the province using the export amount as the weight.

$$expy_j=\sum_k\frac{x_{jk}}{x_j}\times PRODY_K \quad (3)$$

$expy_j$ 、 x_{jk} and x_j denote the technical complexity of China's export in province (city) j, the export value of industry k in province (city) j and the total export in province j, respectively.

The industry export data used in this paper are from the foreign trade database of the National Research Network, and the GDP is taken from the statistical yearbooks of each province and has been adjusted to constant 2000 prices. The range of industries covered is codes 13 to 41 in the National Economic Industry Classification (2017)①.

2. Explanatory variables: Artificial Intelligence

This paper draws on the indicator system construction method of Zao Sun and Yulin Hou(2019) [10] and is transformed on this basis. Comprehensive indicators are constructed from the three dimensions of infrastructure, technology and application, covering a total of 12 specific indicators, such as the scale of Internet users and the revenue of intelligent manufacturing enterprises. In order to objectively and accurately assess the level of AI development in each province in China, this paper adopts the entropy value method to measure it. The design of specific indicators is shown in Table 1.

Referring to the current related research literature, this paper adds the following control variables: economic growth (gdp), foreign direct investment (FDI), environmental regulation (env), infrastructure (linfra), and research and development innovation (pat).

Table 1. Artificial Intelligence Development Indicator System

Target layer	Basic Indicator Layer	Sub-indicator Layer	Indicator Interpretation
AI	Infrastructure (0.1715)	Scale of Internet users	Number of Internet broadband access subscribers/ year-end employed population
		Information infrastructure construction	Mobile switch capacity
		Density of long-distance fiber-optic cable lines	Length/area of long-distance fiber optic cable lines
		Cell phone subscriber scale	Number of cell phone subscribers/year-end employed population
	intelligent Technology (0.2443)	Big Data Acquisition and Processing Capabilities	Information Transmission Software Employment
		Technological Innovation	Number of Artificial Intelligence patents
		Digital Attention	Number of keyword occurrences in government texts
		Intelligent device input	Information transmission fixed asset investment
	Production Applications (0.5842)	Robotics Applications	Number of robots imported
		Technology Market Development	Technology market turnover
		Intelligent Manufacturing Company Revenue	Main Business Revenue of High-tech Enterprises
		Market Competition	Number of Artificial Intelligence Enterprises

3.3. Data sources and descriptive statistics

1. Data Sources

Based on the fact that the statistical data of Tibet is not as systematic and complete as other provinces, which may affect the accuracy and reliability of the study, this paper only analyzes 30 provinces (cities) in the mainland from 2012 to 2021. The data in this paper mainly comes from the statistical yearbook of each province, the national statistical database, the EPS database, the foreign trade database of the National Research Network, the China Customs database, as well as the statistical data and related research results of Enterprise Search. For the individual missing values in the indicator data, the interpolation method is used to deal with them.

2. Descriptive statistics

Before carrying out the empirical analysis, all variables should be analyzed with descriptive statistics, as shown in Table2. The value of the index of the level of artificial intelligence development ranges from 0.014 to 0.540, and the technical complexity of manufacturing exports fluctuates in the range of 10.044 and 11.358, which reflects the existence of regional imbalance in the development of artificial intelligence and the technical complexity of manufacturing exports.

Table 2. Analysis of descriptive statistics

Variable	Obs	Mean	Sd	Min	Max
lexpy	300	10.851	0.2170	10.044	11.358
AI	300	0.0940	0.0830	0.0140	0.5400
FDI	300	0.0180	0.0140	0.0001	0.0800
pat	300	7.6970	10.185	0.5220	76.582
env	300	0.0030	0.0040	0.0001	0.0310
ltrans	300	2.4040	0.1210	2.1320	2.8340
lgdp	300	9.3250	0.4640	8.5980	10.781

Table 3. Benchmark regression

VAR	(1) lexpy	(2) lexpy	(3) lexpy	(4) lexpy	(5) lexpy	(6) lexpy
AI	0.334***	0.309***	0.388***	0.509***	0.504***	0.490***
	(3.900)	(3.590)	(4.450)	(4.960)	(4.880)	(4.730)
env		-2.773**	-3.185**	-3.296***	-3.272**	-2.767**
		(-2.150)	(-2.510)	(-2.620)	(-2.590)	(-2.110)
lgdp			0.139***	0.124***	0.118***	0.114***
			(3.480)	(3.090)	(2.850)	(2.760)
pat				0.002**	0.002**	0.002*
				(2.190)	(2.180)	(1.870)
FDI					0.260	0.227
					(0.660)	(0.570)
ltrans						-0.219
						(-1.370)
Constant	10.820***	10.832***	9.530***	9.638***	9.693***	10.257***
	(1,265.67)	(1,071.67)	(25.470)	(25.720)	(25.220)	(18.240)
Obs	300	300	300	300	300	300
R^2	0.954	0.955	0.957	0.958	0.958	0.958
Province fixed	YES	YES	YES	YES	YES	YES
Time fixed	YES	YES	YES	YES	YES	YES

Note: ***, ** and * indicate that the regression results are significant at the 1%, 5% and 10% confidence levels, respectively, and the numbers in parentheses are standard errors.

4. Empirical Analysis

4.1. Baseline regression analysis

This paper uses stata.16 software to conduct regression tests on data from 30 provinces (cities) in China. The empirical results found that the hausman test p-value is 0.000, which indicates that the double fixed effects model should be selected for regression analysis, the results of the benchmark regression analysis are detailed in Table 3.

Columns (1) through (6) of Table3 present the results of regressions with stepwise introduction of control variables. The coefficient of artificial intelligence on the technological complexity of manufacturing exports is significantly positive at the 1% level. Artificial intelligence provides accurate decision support based on big data analysis, optimizes product design and production processes and analyzes and predicts potential quality problems in real time, which ensures a high standard of quality control throughout the process, thus improving product quality. Therefore, hypothesis 1 of this paper is verified.

4.2. Robustness test

In order to test the reliability and stability of the results, this paper carries out the robustness test of the empirical results by changing the measurement method of the explanatory variables, adding control variables, and dealing with the endogeneity problem in a total of three methods.

1. Replacement of Explained Variables

Drawing on the measurement method of Fuzhu Li et al (2021)[11] scholars, this paper uses the full labor productivity of manufacturing industry (yuan/person) instead of GDP to recalculate the technological complexity of the manufacturing industry's exports, and replaces lexpy with lexp. Table 4 column (1) shows the regression results of replacing the explanatory variables, and the regression coefficient of the level of development of AI is significantly positive, indicating that the conclusion is robust.

2. Adding control variables

Referring to the practice of Xin Shao and Tingli Wu(2022)[12], the control variables marketization degree (market) and trade openness (open) are added, and the existing literature often uses the marketization index measured by GangFan and Xiaolu Wang (2011) [13] to measure the degree of marketization, because the Fan Gang China marketization index report only published the data from 1997-2019, this paper takes the calendar year data, this paper extrapolates the average annual growth rate of the data to get the data of the remaining 2 years. The measure of trade openness in this paper uses the value of total import and export over GDP. The empirical data are from the CSMAR database. The regression results are shown in columns (2) to (3) of Table 4, and the core explanatory variables are still significant, once again proving the robustness of the conclusions.

Table 4. Analysis of robustness test

VAR	(1) lexp	(2) lexpy	(3) lexpy	(4) lexpy
AI	0.430*** (4.910)	0.481*** (4.660)	0.402*** (3.680)	0.771*** (4.260)
market		0.013* (1.810)		
open			0.151** (2.350)	
Constant	10.065*** (21.130)	10.369*** (18.410)	10.276*** (18.430)	9.622*** (14.580)
Obs	300	300	300	270
R^2	0.967	0.959	0.959	0.952
Control fixed	YES	YES	YES	YES
Province fixed	YES	YES	YES	YES
Time fixed	YES	YES	YES	YES

Note: ***, ** and * indicate that the regression results are significant at the 1%, 5% and 10% confidence levels, respectively, and the numbers in parentheses are standard errors.

3. Dealing with endogeneity

There may be a reverse causality between both artificial intelligence and the technological complexity of manufacturing exports, which leads to errors in the structure. Based on this, this paper refers to the methodology of Qunhui Huang et al (2019) [14], which uses the interaction term between the carrying capacity of mobile telephone exchanges in 1989 and the amount of investment in the national ICT industry in the previous year as an instrumental variable, and conducts a regression using 2SLS. The regression results are shown in column (4) of Table 4, where the coefficient of AI is significantly positive, which solves the endogeneity problem of this paper to some extent.

4.3. Regional Heterogeneity analysis

To further explore the differences in the impact of different types of AI on the technological complexity of manufacturing exports, group regressions are conducted based on geographic location.According to the current regional division standards, this paper divides 30 provinces (cities) into three major economic blocks in the east, central and west②.To analyze the extent of the impact of AI on the technological complexity of manufacturing exports.

Table 5. Heterogeneity analysis

VAR	East	Central	West
AI	0.394***	0.735**	0.422
	(3.300)	(2.530)	(1.040)
Constant	7.019***	11.129***	10.179***
	(6.110)	(21.350)	(6.870)
Obs	110	80	110
R^2	0.965	0.990	0.954
Control fixed	YES	YES	YES
Province fixed	YES	YES	YES
Time fixed	YES	YES	YES

Note: ***, ** and * indicate that the regression results are significant at the 1%, 5% and 10% confidence levels, respectively, and the numbers in parentheses are standard errors.

Columns (1) to (3) of Table 5 show the regression results of the impact of AI on the technological complexity of manufacturing exports in the eastern, central, and western regions, respectively, and it is found that the coefficients of the level of AI development in the regressions of the two subsamples in the eastern and central regions are positive and significant, but the coefficients in the western region are not significant. The reason for this may be that the eastern region, as China's economic center of gravity, benefits from its advanced technological innovation and mature high-tech industry, effectively integrates AI technology, optimizes the production process, improves manufacturing efficiency and product quality, and thus significantly improves the technical complexity of manufacturing exports. Through regional cooperation and resource sharing, the central region has strengthened technological exchanges and industrial upgrading, enhanced the international competitiveness of enterprises, and also promoted the technical complexity of exports. However, the western region, limited by insufficient infrastructure and industrial agglomeration, as well as enterprise cognitive and financial constraints, has been relatively slow in the application of AI technology and industrial transformation, and has failed to give full play to the potential of enhancing the technological complexity of manufacturing exports.

5. Conclusions and Policy Recommendations

5.1. Main conclusions

Based on the theoretical analysis, this paper selects 30 provinces in China as research samples from 2012 to 2021 and empirically examines the impact of AI on the technological complexity of manufacturing exports, and the main conclusions are as follows: (1) AI plays a positive role in enhancing the technological complexity of manufacturing exports and is robust; (2) AI effectively enhances the technological complexity of manufacturing exports in the east-central region. Especially in the regions where AI development is more advanced, its facilitating effect is more significant.

5.2. Policy Recommendations

Based on the above conclusions and realities, this paper puts forward the following policy recommendations to promote AI-enabled manufacturing and enhance China's competitive position in the global market.

1. Promote AI to realize high-quality development

In order to comprehensively promote the development of AI, concerted actions are needed at three levels: basic research, technological innovation and application implementation. At the basic level, increase investment in basic AI research and support educational institutions to strengthen and improve AI curricula. At the technical level, original technology research and development should be encouraged, open-source sharing should be promoted, and industry standards should be set to ensure technology quality. At the application level, the focus is on the integration of AI with various industries, exploring new application scenarios, creating new business models, and providing policy incentives by the government to promote AI investment and application. Such a multifaceted promotion will accelerate the maturity and wide application of AI technology and bring innovative power to economic and social development.

2. Implement differentiated strategies

The government should formulate strategies to unleash the potential of AI in improving the technological content of manufacturing exports based on the current state of local AI development and resource advantages. As a leader in economic development, the eastern region should establish cooperation with the central and western regions to promote resource sharing and complementarity, and facilitate the optimization of the manufacturing structure and technological upgrading. For its part, the central and western regions need to accelerate the construction of new infrastructure, and through the "East Counts, West Counts" strategy, realize the effective integration of computing power resources with the Guangdong-Hong Kong-Macao Greater Bay Area and the Yangtze River Delta to enhance the competitiveness of the industrial chain. At the same time, the industry is encouraged to concentrate in regions with a high level of AI development, utilizing its radiation effect to promote close cooperation among all links in the industry chain and improve product quality.

6. Commentary

The scope of manufacturing is as follows: 13 (agro-food processing industry), 14 (food manufacturing industry), 15 (wine, beverage and refined tea manufacturing industry), 16 (tobacco products industry), 17 (textile industry), 18 (textile, clothing and apparel industry), 19 (leather, fur, feather and their products and shoemaking industry), 20 (wood processing and wood, bamboo, rattan, palm and grass products industry), 21 (furniture manufacturing industry), 22 (Paper and Paper Products Industry), 23 (Printing and Recorded Media Reproduction Industry), 24 (Literary, Educational, Dingmei, Sports and Recreational Goods Manufacturing Industry), 25 (Petroleum, Coal, and Other Fuel Processing Industry), 26 (Chemical Raw Materials and

Chemical Products Manufacturing Industry), 27 (Pharmaceutical Manufacturing Industry), 28 (Chemical Fiber Manufacturing Industry), 29 (Rubber and Plastic Products Industry), 30 (Non-Metallic Mineral Products Industry) , 31 (ferrous metal smelting and rolling processing industry), 32 (non-ferrous metal smelting and rolling processing industry), 33 (metal products industry), 34 (general-purpose equipment manufacturing industry), 35 (special-purpose equipment manufacturing industry), 36 (automobile manufacturing industry), 37 (railroads, ship tires, aerospace and other transportation equipment manufacturing industry), 38 (electrical machinery and equipment manufacturing industry), 39 (computers, communication and other electronic equipment manufacturing), 40 (instrumentation manufacturing), 41 (other manufacturing).

The eastern region includes: Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Guangxi, Shandong, Hebei; the central region includes: Hunan, Hubei, Henan, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi; the western region includes: Chongqing, Sichuan, Yunnan, Qinghai, Gansu, Xinjiang, Ningxia, Shaanxi, Guizhou.

Acknowledgment

Funded by: Foshan University 2023 Student Academic Fund Program (No. xsjj202314zsb08).

Guangdong Province Social Science Planning Project (No.GD22CLJ01).

Documentation

[1] K. Guo. Artificial Intelligence Development, Industrial Structure Transformation and Upgrading and Labor Income Share Change[J]. Management World, 2019, 35(07): 60-77+202-203.

[2] Tian Yunhua,Zhou Yanping,Zou Hao et al. The impact of artificial intelligence technology change on international trade[J]. International Trade,2020,(02):24-31.

[3] YUAN Qigang, JI Yongsheng, YU Shuhao. Does Artificial Intelligence Promote Export Product Upgrading of Manufacturing Enterprises? An analysis based on the perspective of technological complexity[J]. Industrial Economics Review, 2022(03):69-82.

[4] Lv Yue, Gu Wei, Bao Qun. Artificial Intelligence and Chinese Enterprises' Participation in Global Value Chain Division of Labor[J]. China Industrial Economy,2020,(05):80-98.

[5] ZHUO Xiaojing,XUE Zhixin,SUN Yiming. How new digital infrastructure affects foreign trade upgrading-Empirical evidence from Chinese prefecture-level and above cities[J]. Economic Science,2020(03):46-59.

[6] Dang Lin,Li Xuesong,Shen Shuo. Digital transformation of manufacturing industry and its export technology complexity [J]. International Trade Issues,2021,(06):32-47.

[7] LI Ya Ya,PAN An. Mechanism and empirical study on the productivity enhancement of China's manufacturing industry by industrial robot imports[J]. World Economic Research, 2017,(03): 87-96+136.

[8] MA Zhaoliang,XU Boqiang,TIAN Shuying. Digital Economy, R&D Innovation and Export Technological Complexity-An Empirical Study Based on Chinese Interprovincial Panel Data[J]. Journal of Anqing Normal University (Social Science Edition),2022,41(03):90-98.

[9] Hausmann,R.,Hwang,J.&Rodrik,D.What you export matters [J]. Journal of Economic Growth,2007,12:1-25.

[10] Sun Zao,Hou Yulin. How industrial intelligence reshapes the labor force employment structure[J]. China Industrial Economy, 2019, (05):61-79.

[11] LI Fuzhu,CAO Youbin,LI Kunze. A study on regional differences and convergence of technical complexity of China's manufacturing exports[J]. Research on Quantitative and Technical Economics,2022,39(04):107-126.

[12] SHAO Xin,WU Tingli. Intellectualization, factor market and high-quality development of industrial economy [J]. Exploration of Economic Issues,2022,(02):112-127.

[13] FAN Gang,WANG Xiaolu,MA Guangrong. The contribution of China's marketization process to economic growth[J]. Economic Research,2011,46(09):4-16.

[14] Huang Qunhui, Yu Yongze, Zhang Songlin. Internet development and manufacturing productivity enhancement: Internal mechanism and Chinese experience[J]. China industrial economy,2019,(08):5-23.