The Impact of Artificial Intelligence on the Green Development of Logistics Industry

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Abstract. Artificial intelligence, as the engine of new quality productivity, is also a strategic technology to lead the future green development. In this paper, panel data of 30 provinces in China from 2013 to 2022 are selected, the development level of logistics industry in each province is measured by using the super-efficient SBM model, and the impact of AI development on the green development of the logistics industry is empirically examined by using the individual fixed effect model. The study found that: (1) there is a "U-shaped" relationship between the application of artificial intelligence and the green development of logistics industry, which is inhibited first and then promoted. (2) Environmental regulation has a moderating effect between AI application and green development of logistics industry. Therefore, we should grasp the opportunity of the development of artificial intelligence, with the help of artificial intelligence technology, carry out the informationization and intelligent transformation of the logistics industry, and realize the green development of the logistics industry.

Keywords: Artificial Intelligence; Greening of the logistics industry; U-shaped relationship; Environmental regulation.

1 Introduction

Accelerating the development of new productivity is the key to promoting high-quality development. At the same time, deepening the application of research and development of big data and artificial intelligence, and carrying out the "artificial intelligence +" action is a new path to achieve development. In the context of the current development of big data, artificial intelligence technology can not only promote the rapid development of the economy, but also in the realization of the green low-carbon transformation of the industry has a more important significance. As the core part of modern service industry, logistics industry not only consumes energy to produce direct carbon emissions in economic activities, but also produces indirect carbon emissions through the use of intermediate goods, causing environmental pollution. Realizing the green development of the logistics industry is an important part of China's "double carbon" goal. It is of great significance to promote the development of logistics informatization and intelligence through the in-depth integration of artificial intelligence and logistics in

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modern society, which further improves logistics efficiency and reduces environmental pollution.

2 Literature Review

In recent years, due to the application of AI technology, Chinese scholars' research on AI has gradually emerged, mostly focusing on the impact of AI applications. There has also been a gradual rise in how AI can empower green development. Shi Dan et al. (2023) believe that AI applications can promote the upgrading of urban industrial structure, enhance the level of urban technological innovation and the level of green and low-carbon, thus promoting the high-quality development of cities[1]. Lv Yue et al. (2023) believe that the emission reduction effect of AI is mainly achieved through three channels: promoting technological innovation, increasing investment in emission reduction equipment, and replacing low-skilled labour[2].For economic growth, Graetz et al.(2015) found, based on an analysis of industry panel data from 1993-2007, that AI promotes economic growth by increasing labour productivity and value added[3]. Aghion and Festré(2017) believe that the development of AI can form a good innovation environment and a perfect technical support system in the industry, and promote other enterprises to accelerate the research and development of new technologies and products, and optimize service levels[4].

By combing through the literature, existing studies have laid the foundation for the impact of AI applications and the green development of the logistics industry, but there are fewer studies that focus their perspectives on the logistics industry and explore the impact of AI on the green development of the logistics industry. The marginal contribution of this paper is to provide a reference for AI-enabled green development of the logistics industry at the theoretical level. In the empirical perspective, it is more economically realistic to explain the impact of AI on green development from a non-linear perspective.

3 Theoretical Mechanism

Artificial intelligence, as an important representative of emerging digital technology, is deeply integrated into various industries, and is not only an important part of the new quality productivity, but also a key technology to promote green development.

The inhibitory effect of AI on the green development of the logistics industry is mainly reflected in the following: first, the energy consumption required for the operation of advanced AI algorithms and data centers should not be ignored; although the overall energy can be saved by optimizing the logistics system in the long term, in the short- and medium-term, the increase in the arithmetic demand may increase the power consumption, which will put forward a higher requirement for the green energy supply of the logistics industry. Secondly, the high initial investment cost of AI and related technologies, if not properly analyzed in terms of cost-benefit and long-term planning, may lead to over-investment of resources in the short term, which fails to be rapidly transformed into significant environmental benefits, and may even aggravate the burden on enterprises due to the failure to adequately consider the payback period, which may in turn lead to the shortage of funds for pollution treatment in logistics enterprises, which is not conducive to the green development of the logistics industry.

The promotion of artificial intelligence for the green development of logistics is mainly reflected in the following: first, artificial intelligence can reduce the intensity of pollution emissions by promoting technological innovation Lv Yue et al. (2023)[5]. Artificial intelligence contains digital algorithms, intelligent applications and other technologies, which can optimize the hardware infrastructure of the logistics industry and provide more accurate digital algorithmic technical support for the logistics industry, which can promote further technological innovation, which in turn is a key force in environmental governance. Secondly, artificial intelligence promotes the green and low-carbon level by updating production equipment. Industrial robots as the representative of artificial intelligence equipment is an important carrier of artificial intelligence technology, with the wide application of artificial intelligence technology, logistics enterprises comply with the trend of intelligent transformation and constantly updated production equipment. These new equipments are generally in line with the concept of green low-carbon, more advanced and environmentally friendly machines and equipments, which play a positive role in promoting energy saving and emission reduction, and realizing green development Dai Xiang (2022)[6]. Thirdly, the development of artificial intelligence can reduce the labor cost of enterprises, leaving capital space for enterprises to invest in pollution treatment equipment, which in turn promotes enterprises to achieve pollution reduction at the end of production, and ultimately improves the enterprise's ability to manage environmental pollution Jin Xiangyi (2023)[7].

Overall, the initial stage of the development of artificial intelligence will lead to the inhibition of the green development of the logistics industry due to the high input and the high energy consumption of artificial intelligence, but with the deepening of the application of artificial intelligence technology, it is able to promote the green development of the logistics industry through the path of technological progress, the update of intelligent equipment, the optimization of the capital structure and other paths. Therefore, this paper proposes the following hypotheses to be tested:

H1: Artificial intelligence on the green development of the logistics industry presents the "U-shaped" characteristics of inhibition followed by promotion.

The regulatory role of environmental regulation in the development of artificial intelligence and logistics industry is mainly manifested in the following ways: first, to encourage investment in sustainable technological innovation. Environmental regulation may set up relevant incentive policies to encourage enterprises to invest in green technology, including the application of artificial intelligence in the logistics field. This will help accelerate the pace of related technology research and development, commercialization and application, and ultimately promote the green transformation of the logistics industry. Second, environmental regulations require enterprises to fulfill their social responsibility and promote the concept of green supply chain. Artificial intelligence can help enterprises accurately track and manage environmental indicators in the supply chain in this process, for example, analyzing and optimizing raw material procurement, product manufacturing, transportation, warehousing and other links in the logistics process through AI algorithms to reduce energy waste and emissions. As a result, this paper proposes the following hypotheses to be tested:

H2: Environmental regulation has a moderating effect between AI and the green development of logistics industry.

4 Empirical Analysis

4.1 Description of Variables

Explained Variables (GLI)

Drawing on the indicator construction ideas of He Jingshi et al. (2021)[8] and Yin Hui (2024)[9], this paper constructs a green logistics indicator system based on the levels of input indicators, desired output indicators and non-desired output indicators, and adopts the super-efficiency SBM model to measure the green logistics efficiency of provinces, which is used to measure the level of the development of the logistics industry in the region. The specific indicator system is shown in Fig. 1

Type of indicator	Specific indicators	unit (of measure)
Input indicators	Number of employees in the logistics industry	man
	Investment in fixed assets in the logistics industry	billions
	Energy consumption	Million tonnes/standard coal
Expected outputs	Cargo turnover	Billion tonnes/km
Non-expected outputs	carbon footprint	tonnes

Fig. 1. Green logistics efficiency

Explanatory Variables (AI)

Drawing on the research methodology of Stan et al. (2023), the density of industrial robots is used to indicate the level of AI application, an indicator that has been widely used in the academic community[10]. Its original data comes from the International Federation of Robotics (IFR). The robot stock data provided by IFR belongs to the country-industry level, and its industry classification standard is not consistent with China. This paper draws on Yan Xueling et al. (2020) to summarize and organize the relevant industries. The total employment by sub-region, employment by sub-industry by sub-region, and national employment by sub-industry involved in this paper's calculations are all from the China Labor Statistics Yearbook. The specific formula for measuring the density of robot installation at the provincial level is as in equation 1:

$$Rob_{it} = \sum_{j=1}^{J} \frac{L_{ijt}}{L_{it}} \times \frac{Rob_{jt}}{L_{it}} \tag{1}$$

where L_{ijt} is the employment of industry j in region i in year t, L_{it} is the employment in region i in year t, Rob_{jt} is the stock of industrial robots in industry j, and L_{it}

is the national employment in industry j. Summing over all industries yields the density of robots installed in region i.

Regulatory Variables (ER)

In this paper, we only consider the impact of government-commanded environmental regulation between AI application and green development of logistics industry, so this paper refers to Wu Peng et al. (2023) and adopts the ratio of industrial pollution control investment to industrial value added to construct the environmental regulation index, the specific formula is as in equation 2:

$$ER_{it} = \frac{Investment_{it}}{Value_{it}} \tag{2}$$

Control Variables (Control)

Control variables include: foreign direct investment (FDI), social consumption level (Consum), labor force in railroad transportation industry (People), industrial structure (Structure), innovation level (Inno). Among them, the FDI level is measured by the percentage of FDI, the social consumption level by the percentage of retail sales of consumer goods, the level of the labor force in the railroad transportation industry by the natural logarithm of the number of people employed in the railroad transportation industry, the industrial structure of each province by the ratio of the value added of the tertiary industry to the GDP, and the level of innovation by the logarithm of the number of domestic invention and patent applications received.

4.2 Model Setting

Based on the previous theory, the nonlinear relationship of artificial intelligence application on the green development of the logistics industry is briefly analyzed. Therefore, this paper further selects the following benchmark model to test the nonlinear relationship of artificial intelligence on the green development of logistics industry, the specific formula is as in equation 3:

$$GLI_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 Contorl_{it} + \gamma_{it} + \varepsilon_{it} \tag{3}$$

4.3 Descriptive Statistical Analysis

Considering the availability of data, this paper selects a total of 30 provinces (except Tibet, Hong Kong, Macao and Taiwan) panel data from 2013-2022, for missing values using linear interpolation, the average growth rate to make up for the data in this paper are the descriptive statistics of the main variables as shown in Fig. 2.

stats	GLI	AI	AI^2	Structure	People	FDI	Inno	Consum
N	300	300	300	300	300	300	300	300
Mean	0.295	17.11	4394	0.510	10.84	0.0172	9.819	0.0083
Sd	0.403	64.15	36247	0.0848	0.701	0.0138	1.333	0.0031
Min	0.027	0.014	0.00021	0.347	8.293	-0.0063	6.254	0.0041
Max	3.295	693.8	481352	0.838	11.84	0.0796	12.52	0.0200

Fig. 2. Results of descriptive statistical analysis

4.4 Benchmark Analysis

The panel data of 30 provinces in China for the period 213-2022 are regressed using the individual fixed effects model, and the results are shown in Fig. 3. The regression results show that both the primary and secondary terms of AI application are significant at the 1% level, and the coefficient of the primary term is negative and the coefficient of the secondary term is positive. Meanwhile, the Utest test results show that the p-value is 0.014, the peak 368.2972 is in the total sample interval, the Utest test is passed, and the U-type relationship significantly exists. From the regression results, it can be seen that the U-shaped relationship between the level of AI application and the green development of the logistics industry shows a first decline, followed by an increase, and hypothesis 1 is verified.

VARIABLES	GLI (1)	GLI (2)	GLI (3)	GLI (4)	GLI (5)
AI	-0.00162***	-0.00160***	-0.00164***	-0.00171***	-0.00166***
	(0.000513)	(0.000507)	(0.000537)	(0.000562)	(0.000537)
AI^2	2.23e-06***	2.21e-06***	2.26e-06**	2.32e-06**	2.25e-06***
	(8.00e-07)	(7.99e-07)	(8.28e-07)	(8.52e-07)	(8.14e-07)
Structure	-0.565	-0.567	-0.641	-0.993	-0.888
	(0.551)	(0.553)	(0.526)	(0.665)	(0.672)
People		-0.0289	-0.0266	-0.0235	-0.0266
		(0.0532)	(0.0531)	(0.0545)	(0.0584)
FDI			-1.014	-1.111	-1.345
			(1.555)	(1.508)	(1.653)
Inno				0.0640	0.0969
				(0.0848)	(0.0781)
Consum					19.66
					(15.09)
Constant	0.601**	0.915	0.945	0.465	-0.0392
	(0.279)	(0.678)	(0.658)	(1.044)	(1.034)
YES	YES	YES	YES	YES	YES
Observations	300	300	300	300	300
R-squared	0.083	0.083	0.085	0.095	0.106
Number of id	30	30	30	30	30

Fig. 3. Benchmark regression results

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, same below

4.5 Robustness Test

To ensure that the model is robust, this paper adopts three tests. First, the OLS model is used to conduct a benchmark regression on the sample, and the results are shown in column (2) in Fig. 4, where the primary and secondary terms are significant at the 1% level and the coefficients are heteroscedastic, the U-shaped relationship still exists, and the original hypothesis is established. Second, in 2017, the State Council issued the New Generation Artificial Intelligence Development Plan, which further promotes the development of artificial intelligence. As a result, the sample interval time is changed to 2017-2022, and the fixed-effects model is reutilized for testing, and the results are shown in column (3) of Table 4, the coefficients of the primary term are significant and negative at the 1% level, and the secondary term is significant and positive at the 5% level, i.e., there is an obvious U-shaped relationship, and the original regression results are robust. Thirdly, considering that there may be persistence and lag in the green development of the logistics industry, a dynamic panel model is used to test the sample again. In the regression results, AR(1) is 0.042, AR(2) is 0.268, there is no second-order autocorrelation in the random perturbation term, and in the Hansen test results, the P-value is 1.000, i.e., there is no over-identification problem, and the model setup is reasonable. The first-order lag term is significantly positive at the 1% level and the coefficients of the primary and secondary terms are heteroscedastic and significant, which again verifies that the original hypothesis is valid and the original results are robust.

Test Methods	return to baseline	OLS model	reschedule	System GMM
AI	-0.00166***	-0.00166***	-0.00124***	-0.000373**
	(0.000537)	(0.000416)	(0.000401)	(0.000179)
AI^2	2.25e-06***	2.25e-06***	1.65e-06**	5.02e-07*
	(8.14e-07)	(6.37e-07)	(6.07e-07)	(2.71e-07)
L. GLI				0.723***
				(0.0831)
Control	YES	YES	YES	YES
Constant	-0.0392	1.656*	-0.818	
	(1.034)	(0.953)	(3.744)	
Individual fixation	YES	YES	YES	YES
Observations	300	300	180	240
R-squared	0.106	0.820	0.084	

Fig. 4. Robustness test results

4.6 Heterogeneity Test

The sample was further divided into three groups, eastern region, central region and western region, and benchmark regression was again conducted on the sample to further explore, whether the geographical development factor affects the relationship between AI and the green development of the logistics industry. The results obtained are shown in Fig. 5. The results show that the development of artificial intelligence on the green development of the logistics industry is obviously influenced by regional development. The non-linear relationship does not exist in the central and eastern regions and is significant at the 5% level in the west. The reason for this is that the central and eastern regions have more complete infrastructure construction, a good foundation of information technology, and rich data resources that provide a good environment for the application of artificial intelligence, which can realize the intelligence and greening of the whole process of logistics more quickly. At the same time, the central and eastern regions have begun to carry out intelligent transformation of all aspects of the logistics system when AI technology was introduced at an early stage, which reduces the initial trial and error costs and has a high level of labor, which is able to promote the further application of artificial intelligence, and avoids the generation of a U-shaped curve. For the western region of China, which is in the early stage of the application of artificial intelligence technology, the green development of the logistics industry is initially inhibited due to the unequal initial inputs and benefits, the lack of technological maturity, and the fact that there may be certain friction costs and environmental costs in the transformation process of the intelligent logistics alternative to the traditional logistics model. With the maturity of the technology, the improvement of the policy and the industry's skillful application of the new technology, AI will further promote the green development of the logistics industry to a new level.

shore	Nationwide	Eastern	Central	Western
AI	-0.00166***	-0.00191*	-0.00375*	-0.00280***
	(0.000537)	(0.000987)	(0.00179)	(0.000680)
AI^2	2.25e-06***	2.50e-06	1.73e-05	2.05e-05**
	(8.14e-07)	(1.50e-06)	(9.48e-06)	(7.47e-06)
Control	YES	YES	YES	YES
Individual fixation	YES	YES	YES	YES
Constant	-0.0392	-1.369	12.08	1.766**
	(1.034)	(2.003)	(6.751)	(0.555)
R-squared	0.106	0.096	0.458	0.643
Number of id	30	11	9	10

Fig. 5. Heterogeneity test results

4.7 Regulatory Effect Test

The previous results confirm that there is a nonlinear relationship between artificial intelligence and the green development of the logistics industry, in order to further explore the relationship between environmental regulation in artificial intelligence and the green development of the logistics industry, this paper constructs the following model 4:

$$GLI_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \beta_3 ER_{it} + \beta_4 AI_{it} \times ER_{it} + \beta_3 Contorl_{it} + \gamma_{it} + \varepsilon_{it} \quad (4)$$

where ER stands for environmental regulation and the coefficients on the interaction terms of ER and AI show the effect of the moderating effect. Columns (3)-(4) in Fig. 6

show the regression results of adding the moderation effect. After centering, the coefficients of the moderating effect are significantly positive at the 10% level and opposite in sign to the coefficients of AI, which can weaken the negative impact of AI development on the green development of logistics industry. The empirical test results are consistent with the hypothesis, and hypothesis 2 is established.

VARIABLES	GLI (1)	GLI (2)	GLI (3)	GLI (4)
AI	-0.00166***	-0.00155***	-0.00156***	-0.00160***
	(0.000537)	(0.000522)	(0.000532)	(0.000557)
AI^2	2.25e-06***	2.06e-06**	2.16e-06**	2.10e-06**
	(8.14e-07)	(7.86e-07)	(7.98e-07)	(7.86e-07)
ER		10.88**	11.42**	11.83**
		(4.171)	(4.465)	(4.571)
AI × ER			-2.48e-05**	
			(1.08e-05)	
cAI × cER				0.00688*
				(0.00375)
Control	YES	YES	YES	YES
Constant	-0.0392	-0.425	-0.395	-0.398
	(1.034)	(1.036)	(1.037)	(1.037)
R-squared	0.106	0.128	0.135	0.133

Fig. 6. Moderating effect test results

5 Conclusion

Based on the above theoretical analysis and empirical tests, this paper draws the following conclusions:

(1)The impact of artificial intelligence applications on the green development of the logistics industry shows a "U-shaped" relationship that decreases and then increases. In the initial stage of the development of artificial intelligence applications, due to a large number of infrastructure construction, resulting in an increase in the energy consumption of artificial intelligence itself, increasing environmental pollution, and at the same time, due to the increase in capital investment in artificial intelligence, so that the logistics enterprise disposable funds to reduce the logistics industry is not conducive to the long-term sustainable development of the logistics industry, but with the continuous deepening of the application of artificial intelligence, artificial intelligence brought about by the technological effect, the labor force substitution effect and the green environmental protection. application of intelligent equipment can contribute to the green development of the logistics industry.

(2)Environmental regulation by the government plays a positive regulatory role between the application of artificial intelligence and the green development of the logistics industry. Environmental regulation puts forward the social responsibility of environmental protection to logistics enterprises, forcing them to invest in green technology innovation. Although environmental regulation will increase the compliance cost of enterprises, the increase in environmental and economic benefits brought about by green technology innovation is enough to offset the compliance cost of enterprises and promote the further development of the logistics industry.

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