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Research on Artificial Intelligence and Trade in Emerging Markets

- A Global Value Chain Perspective

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Abstract: From the perspective of global value chain, this paper explores the correlation between AI and emerging market trade, and analyzes how AI technology affects the trade structure of emerging market countries and their changing position in global value chain. Based on regression analysis and panel data analysis methods, the study comprehensively assesses the specific impact of AI on emerging market trade in terms of production efficiency, product quality, and market entry strategies.This paper proposes that emerging market countries should further strengthen the R&D and application of AI technology, optimize their industrial structure, and actively participate in the innovation cooperation of GVCs. The findings provide an important reference for policymakers to promote emerging market countries to achieve higher quality development in global trade.

Keywords: Artificial intelligence, emerging markets, international trade, global value chains, trade structure optimization.

1. Introduction

In recent years, the rapid development and widespread application of AI technology has become a global concern, and emerging technologies such as artificial intelligence (AI) have become increasingly important as their contribution to solving many of the world's development challenges grows[1]. Emerging technologies such as AI have long been increasingly recognized as important factors in the process of economic growth and development in emerging markets[2][3].

Since the 1990s, with the continuous advancement of the globalization process and the acceleration of technological progress, the world's economic power is crossing national boundaries [4][5], and the status and role of emerging market countries in global trade have become increasingly prominent, becoming an indispensable and important link in the global value chain[6][7]. However, the challenges and difficulties faced by emerging market countries in global trade should not be overlooked. This is because emerging economies are typically characterized by a weak base of basic resources - in terms of human capital, physical capital and infrastructure[8].

The existing literature has conducted a lot of research on how the development of AI technology affects the trade structure of emerging market countries. Brynjolfsson and McAfee in their study emphasized that the widespread use of automated production significantly improves productivity in

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the manufacturing industry[9]. By using AI technology, companies can achieve 24/7 production without human intervention, thus significantly reducing production cycle time and production costs. In the supply chain, Chui, Manyika and Miremadi noted that AI has a wide range of applications in supply chain management, including demand forecasting, inventory management and transportation optimization[10]. Not only that, Ford found that the application of AI technology makes supply chain management more accurate and efficient[11]. In terms of innovation, Acemoglu point out that big data analytics technology enables enterprises to gain a deep understanding of market demand and consumer preferences, thereby guiding the design and development of new products[12]. By analyzing large amounts of market data, companies can predict future market trends and design innovative products that better meet consumer needs.

However, although the rapid development and application of AI technology has become a new engine for the global economy, there are still many unknown and unexplored questions about its relevance to trade in emerging markets. Under the perspective of global value chains, how to understand and assess the impact of AI technology on emerging market trade, as well as the positioning and role of emerging markets in global value chains, has become one of the questions that need to be answered urgently by both academics and practitioners at present.

Therefore, this study aims to explore the correlation between AI technology and emerging market trade, as well as its position and role in global value chains from the perspective of global value chains. It explores the interrelationships between variables such as the adoption of AI technologies, trade performance of emerging markets and participation in global value chains in an empirical study and makes recommendations.

2. Research on trade in emerging markets in the context of artificial intelligence

2.1. Reduced trade costs

Artificial Intelligence technology plays a significant role in reducing production costs. Through automation and intelligent manufacturing, enterprises can reduce labor costs and improve productivity, thus reducing production costs[13][14]. For example, AI technology can optimize production processes, reduce resource wastage, and improve raw material utilization, thereby reducing production costs[15][16]. In addition, AI technology can extend equipment life through predictive maintenance, reducing equipment failures and maintenance costs[17]. For example, Vietnamese manufacturing companies have achieved significant reductions in production costs by introducing AI technology for smart manufacturing.

For example, a logistics company in Brazil has significantly reduced transportation costs by applying AI technology to optimize transportation routes and scheduling. The company used AI algorithms to analyze traffic conditions and weather data to select the best transport routes and times, reducing transport time and fuel consumption, and thus lowering transport costs.

2.2. Increased market access and competitiveness

Artificial intelligence technologies can help businesses in emerging market countries improve market access. Through data analytics and smart marketing, companies can better understand market demand and consumer preferences and develop effective market access strategies. An Indonesian food company has successfully entered the European market by applying AI technology for market analysis and smart marketing[18]. The company used AI technology to analyze the consumer trends and competitive landscape in the European market to develop an accurate market entry plan. Through intelligent marketing, the company increased the awareness and acceptance of its products in the European market and successfully entered the European market and achieved significant market share.

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3. Hypotheses development

Theoretically, there is a dual impact of AI on emerging market trade. On the one hand, AI can enhance the productivity and innovation capacity of emerging market countries[19]. On the other hand, AI may exacerbate the technological divide and trade imbalance between them and developed countries.

In GVCs, it is widely believed that AI technologies have significantly improved production and operational efficiency through automation and intelligence. By applying it, emerging market countries are able to better respond to changes in the international market and fluctuations in demand, improve the stability and reliability of the supply chain, and enhance trade competitiveness[20][21]. Therefore, it is believed that the correlation between the level of AI technology application and emerging market trade is moderated by the degree of participation in the global value chain, and countries or regions with a high degree of participation are more likely to benefit from the application of AI technology[22].Summarizing the above analysis, this paper proposes the hypothesis:

Hypothesis 1: There is a positive correlation between the level of AI technology adoption and trade performance in emerging markets.

By reducing trade barriers and tariffs, trade openness improves the competitiveness of exported products and thus promotes export growth. Therefore, it is believed that the degree of trade openness of emerging market countries is positively correlated with their trade performance. Countries with a higher degree of trade openness are more likely to attract foreign investment and technology transfer, promote their trade growth and optimize their trade structure. Such openness contributes to greater connectivity with global markets, thereby enhancing the country's position in the global value chain. Summarizing the above analysis, this paper proposes the hypothesis:

Hypothesis 2: There is a positive correlation between the degree of trade openness of emerging markets and their trade performance.

Participation in GVCs can bring multiple benefits to emerging market countries, including technology transfer, knowledge spillovers, productivity gains and market access opportunities. Firms and countries with high GVC participation are better able to utilize AI technologies to enhance trade performance[23].

Therefore, the moderating role of GVC participation in the trade correlation between AI technology adoption and emerging markets is considered. Countries or regions with a high degree of participation in GVCs are usually more likely to benefit from the application of AI technologies by absorbing advanced technologies and engaging in cross-border cooperation. Summarizing the above analysis, this paper proposes the hypothesis:

Hypothesis 3: Global value chain participation plays a moderating role in the trade correlation between AI technology adoption and emerging markets.

4. Empirical analysis

4.1. Sample Selection and Data Sources

The data sample for this study was selected from emerging market countries, specifically China, India, Russia, Indonesia, Thailand, Singapore, the United States, France, the United Kingdom, and Japan, for the 11-year period from 2013 to 2023, which were chosen based on their importance in the global value chain and their rapid development in the field of artificial intelligence.

Unless otherwise stated, data for variables are obtained from national statistical offices, statistical yearbooks, the UN Comtrade database, labor yearbooks, the World Bank Database, the Global AI Index, the Heritage Foundation, and others.

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4.2. Variable design

(a) Explained variables

The import and export trade volume of emerging market countries in period t is used as an explanatory variable. This paper studies the impact of artificial intelligence technology on the import and export trade of emerging market countries. By studying the impact of each explanatory variable on the trade volume of emerging markets, the impact mechanism of foreign trade is more clearly analyzed, which is conducive to China's balanced development of foreign trade, a dialectical view of the situation of import and export trade of emerging market countries, injecting kinetic energy for the innovative development of global trade, and providing suggestions for the import and export trade policies of emerging market countries, with data from UN Comtrade database.

(b) Core explanatory variables

The level of artificial intelligence in emerging market countries is used as the core explanatory variable. The level of artificial intelligence, according to the existing research literature, the indicators to measure the level of artificial intelligence mainly include the number of industrial robots installed, the number of artificial intelligence patents and the level of information technology application. Some scholars, such as Wang Lihua [24][25], have adopted the "investment in fixed assets and gross product of the whole society in the information transmission, computer services and software industry" to measure the level of AI development. This study draws on the ratio of social fixed asset investment in the information transmission, computer services and software industry to GDP as a measure of the level of AI development.

(c) Control variables

According to that, this study adds the following control variables to the econometric model: trade openness (expressed by total exports and imports/GDP), stock of outward foreign direct investment (OFDI), economic freedom, financial freedom, labor force size.

(d) Data description

The study years for this research are 2013-2023, and data for variables were obtained from national statistical offices, statistical yearbooks, the UN Comtrade database, and labor yearbooks, among others, unless otherwise noted.

4.3. Descriptive statistics of variables

The sample data used in this paper are taken from relevant reports issued by individual countries for the relevant years, and some of the data are logarithmized.

Table 1: Sample data(Partial data logarization)

Variant	Observed value	Average value	Standard deviation	Minimum value	
Trade Performance	102	17.791	2.579	15.03	24.48
Artificial Intelligence	110	1.714	1.01	0.28	4.36
GDP	100	14.697	1.24	12.64	17.05
Freedom of Trade	100	80.026	6.91	63.6	95
Freedom of Commerce	100	75.44	14.81	37.3	97.1
Freedom of Labor	100	66.23	16.595	41.2	98.5
Freedom Monetary	100	76.26	6.71	57.3	90.6

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4.4. Model construction

In conducting the fixed effects model regression, which panel data model is suitable for the selected sample data should be judged by the economic phenomenon under study as well as the results of the F-test and Hausman test. At present, the theoretical research will generally take the fixed effect as the starting point of the study, and then test the advantages and disadvantages of mixed regression, fixed effect and random effect. f-test to judge the choice of mixed regression or fixed effect, if the test of the p<5%, then should be used in the fixed effect regression, if the p>5%, then choose the mixed regression; Hausman test to judge the choice of fixed effect or random effect, when the p<5%, then use the fixed effect, otherwise use the random effect. fixed effects and vice versa with random effects.

On the basis of summarizing the existing studies and combining the variables selected and the problems to be studied in this paper, the following general panel model is established with trade performance as the dependent variable and artificial intelligence as the independent variable:

$$Y_{it} = \partial + \beta_1 X_{1it} + \beta_2 X_{2it} + \varepsilon \quad (1)$$

Where Yit is the trade performance of each country in period t respectively, X1it is the main explanatory variable, specifically the level of artificial intelligence; X2it is the set of all control variables, α, β1, β2 are the parameters to be estimated, and ε is the error term.

In order to more precisely understand the path of the impact of AI on the import and export trade of emerging market countries, the mediating effect model is utilized for empirical analysis. The global value chain participation is used as a mediating variable to study the impact path of AI level → emerging market import and export trade (Trade)".

F-test and Hausman test are applied to the above sample model using Stata16.0. In the model (1), the P-value of the F-test is 0.000, which indicates the existence of individual effects, because the F-test does not take into account the clustering of the robust standard error, so the other LSDV method is used to verify the P-value of the test is 0.000, which indicates that there are unobservable individual effects in the samples, so we should choose the fixed effects rather than mixed regression. Then further Hausman test, P value is 0.1625, so the original hypothesis of random effects can be accepted, and reject the fixed effects. However, in combination with the economic phenomenon, some scholars point out that usually when the regression results are confined to some specific individuals, the fixed effect model is more appropriate than the random effect model, thus preferring the fixed effect model, so this paper outputs the estimation results of both the random effect and the fixed effect models in the baseline regression process.

4.5. Benchmark regression

4.5.1. Heteroscedasticity test

Before the benchmark regression need to determine the nature of the sample, it is possible that due to the existence of heteroskedasticity, resulting in the fitting equation in the independent variable is small can be more accurate estimation of the dependent variable, while in the independent variable is large when it is difficult to accurately estimate the value of the dependent variable, so from an overall point of view, the existence of heteroskedasticity makes the efficiency of the method of least squares becomes low. Judging from the test results, if there is no heteroskedasticity, the least squares method can still be used for regression analysis; if there is heteroskedasticity, the least squares method is inefficient at this time, and the method of "Least Squares + Robust Standard Errors" should be used, or the feasible Generalized Least Squares method. Stock and Watson[26]recommend that least squares + robust standard error should be used in most cases. The results of the heteroskedastic White's test as well as the BP test are shown below:

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Table 2: Heteroscedasticity test results

Test Methods	Test Statistic	P 值
White's test	chi2(27)=78.95	Prob > chi2=0.0000
BP test	chi2(1) = 15.31	Prob > chi2=0.0001

4.5.2. Estimation of fixed effects and random effects regression results

The regression analysis of model (4.1) using fixed and random effects is shown in the table below:

Table 3: Fixed Effect

VARIABLES	(1) trade performance	(2) trade performance	(3) trade performance	(4) trade performance	(5) trade performance	(6) trade performance
Artificial Intelligence	0.198*	0.036	0.062	0.103***	0.103**	0.102**
	(1.94)	(0.98)	(1.36)	(3.28)	(3.23)	(3.21)
GDP		0.850***	0.886***	0.941***	0.936***	0.887***
		(11.63)	(12.18)	(11.01)	(8.62)	(7.45)
Freedom of Trade			-0.012**	-0.010**	-0.010**	-0.010**
			(-2.70)	(-2.44)	(-2.55)	(-2.66)
Freedom of Commerce				-0.004**	-0.004**	-0.004**
				(-2.36)	(-2.35)	(-2.37)
Freedom of Labor					-0.000	0.000
					(-0.12)	(0.13)
Freedom Monetary						0.006
						(1.24)
Constant	17.46***	5.177***	5.587***	4.854***	4.949**	5.182**
	(101.14)	(4.85)	(5.69)	(4.15)	(3.13)	(3.08)
Observations	102	100	100	100	100	100
Number of id	10	10	10	10	10	10
R-squared	0.088	0.487	0.529	0.553	0.553	0.562

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
stochastic effect

VARIABLES	(1) trade performance	(2) trade performance	(3) trade performance	(4) trade performance	(5) trade performance	(6) trade performance
Artificial Intelligence	0.201**	0.032	0.058	0.102***	0.102***	0.101***
	(2.06)	(0.80)	(1.09)	(3.11)	(3.15)	(3.26)
GDP		0.879***	0.920***	0.967***	0.967***	0.935***
		(10.91)	(11.22)	(9.41)	(7.87)	(6.51)
Freedom of Trade			-0.013***	-0.010**	-0.010**	-0.011***
			(-2.69)	(-2.43)	(-2.52)	(-2.59)

DOI: 10.54254/2754-1169/118/2024.18578

Table 3: (continued).

Freedom of Commerce				-0.004**	-0.004**	-0.004**
				(-2.23)	(-2.21)	(-2.18)
Freedom of Labor					-0.000	0.001
					(-0.02)	(0.23)
Freedom Monetary						0.005
						(1.09)
Constant	17.397***	4.760***	5.119***	4.485***	4.496***	4.539***
	(22.27)	(5.13)	(5.47)	(3.56)	(2.84)	(2.71)
Observations	102	100	100	100	100	100
Number of id	10	10	10	10	10	10
	0.087	0.487	0.529	0.553	0.553	0.562

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.6. Robustness Tests

In conducting the robustness test of the full sample data, the robustness test can be tested by replacing the variable measurement, replacing the control variables and randomly selecting sub-samples, etc. The three methods do not have obvious differences, and all of them are the verification of whether the original model is robust or not, and in this paper, the main consideration is to randomly select 80% of the sub-samples to conduct the robustness test. From the results of the robustness test, it can be seen that the fixed-effects model construction passes the robustness test, and the regression results of the original model are robust.

Table 4: Robustness Check

VARIABLES	(fixed effects) trade performance	(Random effects) trade performance
Artificial Intelligence	0.146**	0.143***
	(2.94)	(3.19)
GDP	0.784***	0.860***
	(4.78)	(4.42)
Freedom of Trade	-0.009**	-0.009***
	(-2.99)	(-2.83)
Freedom of Commerce	-0.004**	-0.004**
	(-2.29)	(-2.12)
Freedom of Labor	0.001	0.001
	(0.19)	(0.33)
Freedom Monetary	0.008	0.007
	(1.51)	(1.14)
Constant	6.408**	5.341**
	(2.79)	(2.37)
Observations	80	80
Number of id	10	10
R-squared	0.559	0.557

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4.7. Tests of the mediating effect mechanism

Table 5: Mechanism test for intermediation effects

VARIABLES	(1) global value chain	(2) trade performance
Artificial Intelligence	0.132*	0.102**
	(2.17)	(3.21)
Constant	5.753***	5.182**
	(54.48)	(3.08)
control variable	yes	yes
Observations	59	100
Number of id	8	10
R-squared	0.085	0.562

	Coef	Std Err	Z	P>|Z|
Sobel	.40886216	.22194409	1.842	.06544803
Goodman-1 (Aroian)	.40886216	.22973667	1.78	.0751252
Goodman-2	.40886216	.21386777	1.912	.05590799

	Coef
a coefficient	-.052679
b coefficient	-7.76137
Indirect effect	.408862
Direct effect	.776395
Total effect	1.18526
Proportion of total effect that is mediated	.34495644
Ratio of indirect to direct effect	.52661602
Ratio of total to direct effect	1.526616

sgmediation tv,mv(lnGVCsr global value chain) iv(specific value) cv(TradeFreedom BusinessFreedom LaborFreedom)

(1)Building enterprise AI quality metrics

Considering that the number of enterprise AI patent applications used in this paper may have certain measurement errors, which leads to the inaccuracy of the estimated coefficients, and that the empirical analysis of most scholars indicates that Chinese enterprises pursue the "quantity" of patents and ignore the "quality" of patents in the innovation process (Jie and Zheng Ping)[27], this paper refers to the existing literature and adopts the number of AI invention patent applications, the number of AI patent families, and the combined value based on data availability. "Therefore, with reference to the existing literature and based on data availability, this paper adopts the number of AI invention patent applications, the number of AI patent families, the number of patents with combined value-weighted value, and the number of patents with citation-weighted value to measure the quality of enterprises' AI patents (all natural logarithms are taken after adding 1). These four new patent metrics measure the quality of AI patents, and therefore highlight the level of an enterprise's AI technology (innovation) more than the number of AI patent applications. The regression results for the AI patent quality indicators show that the core finding that AI promotes trade in emerging markets is robust.

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5. Conclusion

This study finds that the improved level of AI technology significantly contributes to the export and import trade performance of emerging market countries. AI technology enhances the international competitiveness of firms by improving production efficiency, optimizing supply chain management and facilitating product innovation, thus promoting export growth and import structure optimization. This finding is consistent with the existing literature and suggests that AI technologies play an important role in enhancing the trade performance of emerging market countries. GVC participation plays a significant mediating role between the level of AI technology and emerging market trade performance. A high level of GVC participation enables emerging market countries to better apply AI technologies to improve their productivity and innovation, thereby enhancing their international competitiveness and trade performance.

5.1. Potential links between productivity growth and AI

Research suggests that one potential reason for lower productivity growth is the limited capacity of economies to absorb and effectively utilize new technologies, particularly artificial intelligence. The introduction of new technologies requires time to build up sufficient capital stock, time to fully utilize AI investments, and time to acquire skilled personnel and business practices to realize the overall effects, especially for complex technologies that have economy-wide implications. It also takes time to fully capitalize on AI investments and to develop skilled technical personnel and business practices.

The government can promote the effective application of AI technology by strengthening investment in education and promoting vocational training to improve the skill level and innovation ability of the labor force.

5.2. Potential links between supply chain optimization and artificial intelligence

Research has shown that AI technology can optimize the links and nodes in the supply chain network and improve overall supply chain efficiency. Enterprises with high GVC participation have easier access to advanced technologies and management experience. Through GVC participation, companies are able to build more resilient supply chain networks. By monitoring and predicting potential risks in the supply chain in real time, AI technology helps enterprises take measures in advance to avoid or mitigate the impact of supply chain disruptions, enabling them to adjust their supply chain strategies faster and maintain the continuity and stability of the supply chain.

Governments can achieve trade freedom by reducing trade barriers, simplifying import processes, lowering import tariffs and encouraging the import of advanced technology and equipment.

5.3. Potential links between product innovation optimization and artificial intelligence

Research has shown that AI technologies can enhance technological innovation, market agility and collaborative innovation, thereby strengthening their international competitiveness and market performance. Firms with high GVC participation are better able to access and apply these technologies to enhance their technological innovation capabilities and simulate product performance. And by promoting cross-sector and cross-border collaborative innovation, they enhance product innovation capabilities.

Governments can provide innovation and R&D support, encourage enterprises to invest in the development and application of new technologies. Cooperation between universities, research institutions and enterprises should be promoted to facilitate the industrialization of research results.

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