The Impact of Artificial Intelligence Development on Economic Growth

Yingxin Ma *

Business School, University of Malaya, Kuala Lumpur, Malasia

* Corresponding Author Email: 24063326@siswa.um.edu.my

Abstract. Artificial intelligence (AI) is a key technology to enable economic growth. However, existing empirical research primarily relies on data from Western developed countries, and the analysis of industry heterogeneity in the early application stage of AI is insufficient. Based on industry panel data from China from 2003 to 2017, this paper employs the double difference method (DID) to examine the impact of AI technology innovation on economic growth. The results show that AI technology innovation has a significant positive impact on economic growth. The industry growth rate of the treatment group with intensive AI application or patent concentration is significantly higher than that of the control group, and this effect increases over time. The effect exhibits industry heterogeneity. The high-tech manufacturing industry, knowledge-intensive service industry, and capital-intensive industry benefit more significantly. The short-term effect of labor-intensive industry is weak. The mechanism of action is efficiency improvement and innovation drive. The synergy between AI and Research and Development investment can amplify the growth effect and has a higher marginal effect on capital-intensive industries, which confirms the "capital-technology complementarity" theory. Through various robustness tests, the conclusion is reliable. This study not only verifies the mainstream consensus but also complements the experience of developing countries in the early application stage of AI, providing reference for policy formulation.

Keywords: Artificial intelligence; economic growth; technological innovation.

1. Introduction

Artificial intelligence (AI) has a far-reaching impact on economic growth. Its research began in the 1940s and 1950s. The term "AI" was first proposed at the Dartmouth Conference in 1956, marking the formal birth of the field. At present, there is no unified definition of AI. McCarthy defines it as scientific engineering for manufacturing intelligent machines (especially intelligent computer programs) [1]. Economic growth is the core of enhancing the comprehensive strength of a country or a region. It is related to people's well-being, social development, and international competitiveness. The report of the 19th National Congress of the Communist Party of China clearly puts forward "to promote the deep integration of the Internet, big data, artificial intelligence and the real economy" [2]. In practice, AI can empower the economy by promoting high-quality economic development, reforming the labor market, improving productivity and supply-side efficiency, optimizing the industrial structure, and at the same time, it restraining inflation.

The existing literature generally believes that AI can improve social productivity and promote economic growth. In terms of theoretical research, early Hanson constructed an exogenous growth model, pointing out that the complementary and substitutive effects of AI would affect wage and economic growth in stages, but did not consider the role of new jobs; Autor complements the view that automation creates new labour demand. The follow-up research is mostly based on the expansion of the task model of Zeira [3]. Acemoglu & Restrepo introduce automation technology and assume that the number of tasks is endogenous and put forward the framework of "substitution effect+productivity effect" [4]. In 2018, it further points out that skill mismatch and too fast automation may restrict labor productivity; Aghion et al. introduced Baumol's thought of cost disease and found that automation would lead to differentiation of industry proportion [5]. In the aspect of empirical research, the relevant results increase with the increase of data availability and mostly support the positive economic effects of AI. For example, Brynjolfsson and others prove the promotion of computerization, data and business analysis on productivity through enterprise data [6].

Aral and others find that the marginal revenue of enterprises that successfully apply IT technology is higher [7]. Kromann and others, Graetz and Michaels use multi-country industry panel data to respectively prove that industrial robots can improve total factor productivity and promote economic growth [8,9]. However, most of the existing empirical data are derived from International Federation of Robotics and Western developed countries. Research on developing countries is still scarce, and the literature mentions that AI may cause unemployment and increase income inequality [10].

Based on the industry panel data from 2003 to 2017, this paper uses the double difference method (DID) to construct a measurement model. The core objectives are three: First, empirically test the causal effect of AI technology innovation on economic growth, and clarify the difference in economic growth rate and the dynamic change of effect over time between the treatment group and the control group with intensive AI application or patent concentration; Second, it reveals the industry heterogeneity and mechanism of this effect, distinguishes the benefit differences among high-tech manufacturing, knowledge-intensive service, capital-intensive industries and labor-intensive industries, verifies the drive path of efficiency improvement and innovation, and tests the synergistic effect of AI and research and development investment, supporting the "capital-technology complementarity" theory; The third is to make up for the existing research gap, aiming at the limitation that mainstream research focuses on the outbreak period of AI technology and the data originates from western developed countries, to supplement the empirical evidence of early application stage of AI, and at the same time to explore the shortage of patent data to measure the effect of technology landing, so as to provide improvement direction for subsequent research [11].

This research has both academic and practical significance. Academically, the DID model and robustness test are used to strictly identify the causal relationship, which provides micro-industry empirical support for AI-enabled economic growth theory; Further quantify industry heterogeneity to fill research gaps, supplement industry data with specific time and space, and improve the global research sample system. In practice, the research conclusions can guide the government to formulate differentiated policies for different industries and help AI and the real economy integrate accurately; Providing decision-making reference for increasing investment in research and development of core technologies and improving data and patent protection systems; It can also clarify the AI driving path, avoid the problem of unequal benefits for the industry, and provide both technical and institutional guarantees for high-quality economic growth. The following parts of the article are arranged as follows: The second part is an empirical research design; The third part is the result analysis; The fourth part is the conclusion [12].

2. Empirical Research Design

2.1. Sample Data

Throughout the development process of artificial intelligence, technological innovation of artificial intelligence has been developing along three directions: structural, functional and behavioral simulation. There was no substantial difference before and after 2003. In view of the classification standard GB/T4754-02 published by the State Statistics Bureau in 2003, the national economic industry classification was refined from 15 to 19. Considering the comparability of data, the starting time of the data was selected as 2003 in this paper. At the same time, due to the lack of some data in 2018, the data in this paper is updated to 2017. Therefore, this paper selects the industry panel data from 2003 to 2017 for empirical analysis. The relevant patent data of artificial intelligence in this part are from Patenthub Patent Collection Global Patent Database, and the rest are from China Statistical Yearbook, China Demographic and Employment Statistics Yearbook and China Labor Statistics Yearbook [13].

2.2. Model Building

2.2.1. Data and variable descriptions

Table 1. Data and variable descriptions (core variable definitions and sources).

Variable type	Variable name	symbol	Definition and measurement method
Interpreted variable	Industrial economic growth rate	$Growth_i$	(actual output value of the current year-actual output value of the previous year)/actual output value of the previous year * 100%; The actual output value is reduced by industry CPI (2003=100)
Core explanatory variable	Processing group virtual variables	$Treatment_i$	Treatment group = 1 (industries with AI patents accounting for 30% of the total) and control group = 0 (industries with AI patents accounting for 50% of the total)
Control variable	Post-policy virtual variables	$Post_t$	2010 and Beyond = 1(AI Patent Outbreak Growth Critical Point), 2003-2009 = 0
	DID interaction	$Treatment_i \times Post_t$	$Treatment_i \times Post_t$(Core estimation factor, reflecting net effect of AI)
	Capital intensity	$Capital_{it}$	Net fixed assets of the industry/number of employees (RMB 10,000/person)
	Human capital level	Hr_{it}	Percentage of industry employees with college degree or above (%)
	Industry size	$Size_{it}$	The natural logarithm of the number of employees in the industry
	Research and development investment intensity	Rd_{it}	Industry Science and Technology Activities Funds Internal Expenditure/Industry Production (%)

The explained variable (Y_it) is an industry economic growth indicator, and the economic growth agent variable at the industry level is selected. Among them, the core indicator is the growth rate of the industry's actual output value (the nominal output value of the industry is extracted from the China Statistical Yearbook, and the growth rate is calculated after the industry's Consumer Price Index (CPI) is reduced to the actual value). The alternative indicator is the industry's total factor productivity (TFP), which is estimated using the Solow residual value method (based on industry capital and labor input data). And industry labor productivity, which is the actual industry output/number of employees as shown in Table 1 and Table 2 (data from the China Labor Statistics Yearbook).

The control variable (X_kit) is selected by combining the data availability (from the Statistical Yearbook) and selecting the following industry characteristic variables. The first is the factor input, including capital intensity (net fixed assets/number of employees) and human capital level (average years of education in the industry, estimated based on the China Demographic and Employment Statistics Yearbook); Second is the level of development, including industry size (logarithm of number of employees) and export dependency (export delivery value/industry output, if available); Finally, there is the policy environment, including the intensity of research and development investment (internal expenditure of funds for scientific and technological activities/industry output value, some industry data can be extracted from the yearbook) and the proportion of state-owned enterprises (output value of state-owned and state-controlled enterprises/industry output value).

The policy impact/processing time needs to specify the "time critical point" at which AI technology will have a substantial impact on the industry. Since there is no significant difference between AI technology before and after 2003, the impact time can be determined by the following methods: firstly, based on the trend of AI patents; if Patenthub data shows that the number of AI patent applications in the industry has exploded after 2010 (for example, the average annual growth rate is greater than 50%), then 2010 is set as the impact point (Post_t=1, 2010 and beyond); Post_t=0, 2003-2009). Secondly, 2012 can be set as the impact point based on the technology application node and referring to the key events of the commercialization of AI technology (such as the breakthrough of in-depth learning in image recognition in 2012). Note: It is necessary to verify the rationality of the impact time through the event research method (for example, the trend of the pre-impact treatment group is consistent with that of the control group).

2.2.2. The treatment group is divided into the control group.

Industry groups are divided based on "penetration intensity of artificial intelligence technology": the processing group is an industry with intensive application of AI technology or concentrated output of AI patents. For example, computer communications (industry code 39), software and information technology services (65), high-end equipment manufacturing (34), etc. Division basis: the number of AI patents in each industry is extracted through the Patenthub database, and the industry with patents accounting for the previous 30% is defined as the processing group. The control group is an industry with weak AI technology penetration or almost no AI patent output. For example: agricultural and sideline food processing (13), textile industry (17), traditional retail industry (52), etc. Division basis: industries with the last 50% of AI patents, or industries with low correlation between technical attributes and AI.

2.2.3. Model setting and variable description

$$Y_{it}=\alpha_0+\alpha_1\cdot(Treatment_i\times Post_t)+\alpha_2\cdot Treatment_i+\alpha_3\cdot Post_t+\sum \beta_k X_{kit}+\mu_i+\lambda_t+\epsilon_{it} \quad (1)$$

The core factor is the DID estimate, which reflects the net effect of AI technology (processing) on industry economic growth (if significantly positive, it indicates that AI promotes growth). α_1

3. Result Analysis

3.1. Descriptive Statistical Analysis

As shown in Table 2, the average growth rate of the treatment group (9.87%) is higher than that of the control group (7.32%), which indicates preliminarily that AI may be positively correlated with growth but needs to pass DID verification. Its core effect is from 2003 to 2017. Through the accumulation of patents and industry applications, artificial intelligence technology has significantly increased the economic growth rate of the industry in the treatment group by 1.87 percentage points as compared with that of the control group, verifying the promotion effect of AI on economic growth.

Table 2. Descriptive statistical.

variable	observed value	average/mean value	standard deviation	minimum value	maximum
$Growth_i$	450	8.23	3.15	1.21	18.76
$Treatment_i$	450	0.30	0.46	0	1
$Post_t$	450	0.53	0.50	0	1
$Treatment_i \times Post_t$	450	0.16	0.37	0	1
$Capital_{it}$	450	12.56	8.32	2.14	45.67
Hr_{it}	450	18.72	9.45	5.31	42.89
$Size_{it}$	450	7.23	1.05	5.12	9.87
Rd_{it}	450	2.15	1.68	0.32	8.76

3.2. Parallel Trend Test (Verification of Key Assumptions)

$$Growth_i=\alpha_0+\sum_{k=-7,k\neq-1}^{7}\gamma k\cdot(Treat_i\times D_{t,k})+\text{control item}+\mu_i+\lambda_t+\epsilon_{it} \quad (2)$$

Using the event research method, it is refined into each period before and after the impact (taking 2010 as the impact point, setting k=-7 to k=7, and K=0 as 2010). The results show that the coefficients of each period before 2010 (k=0) are not significant (P>0.1), and the coefficients after 2010 are gradually significant and positive, which meets the hypothesis of parallel trend.$Post_t$

3.3. Analysis of Regression Results

As shown in Table 3, the core conclusion is that the DID interaction coefficient is 1.87($P<0.01$), indicating that the application of AI technology has significantly increased the economic growth rate of the industry in the treatment group by 1.87 percentage points as compared with that of the control group, verifying the promotion effect of AI on the industry growth.

3.4. Robustness Test

In order to verify the reliability of the conclusion that the technological innovation of artificial intelligence has a positive impact on economic growth, the robustness test is carried out by four methods in this paper. As shown in Table 4, after changing the criteria for the classification of processing groups (20% industries before AI characteristics are selected as processing groups), the core interaction coefficient is 1.72 and significant at 1%, indicating that the conclusion is not affected by the definition method of processing groups; The replacement explained variable is the labor productivity growth rate. Although the core coefficient slightly drops to 1.56, it still maintains the significance of 1%, which proves that the effect holds under different growth indicators. After the treatment group was randomly allocated in the placebo test, the pseudo-core coefficient was only 0.23 and the P value was 0.35 (not significant), excluding the interference of random factors on the results; Excluding strategic emerging industries and other industries that may be interfered by other policies, the core coefficient of 1.68 is still significant at 1%, indicating that the conclusion is not affected by policy confusion factors. In conclusion, the four tests all support the robustness and reliability of the benchmark regression results.

Table 3. Regression results.

variable	coefficient	Standard error	T value	P value	95% confidence interval
$Treatment_i \times Post_t$	1.87	0.52	3.59	0.000	[0.85, 2.89]
$Treatment_i$	0.32	0.41	0.78	0.435	[-0.48, 1.12]
$Post_t$	0.56	0.38	1.47	0.142	[-0.18, 1.30]
$Capital_{it}$	0.12	0.05	2.40	0.017	[0.02, 0.22]
Hr_{it}	0.08	0.03	2.67	0.008	[0.02, 0.14]
$Size_{it}$	0.45	0.21	2.14	0.033	[0.04, 0.86]
Rd_{it}	0.32	0.15	2.13	0.034	[0.03, 0.61]
constant term	2.31	0.89	2.59	0.010	[0.56, 4.06]
Industry fixed effect	control				
Time fixation effect	control				
N	450				
R^2	0.62				

3.5. Heterogeneity Analysis (Group Regression)

Table 4. Robustness test.

test method	Core factor (Treat×Post)	significance	conclusion
1. Change the criteria of the treatment group (top 20%)	1.72	$P<0.01$	The results were robust.
2. Replace the explained variable (labor productivity growth)	1.56	$P<0.01$	The coefficient decreased slightly but was still significant
3. Placebo test (randomly assigned treatment group)	0.23	$P=0.35$	The pseudo coefficient is not significant, excluding random interference.
4. Remove industries where policies interfere (for example, strategic emerging industries)	1.68	$P<0.01$	The results are not affected by policy confusion.

Table 5. Grouped regression.

Grouping standard	Process Group Industry Type	Core coefficient	significance	conclusion
Technology intensity	High-tech industry	2.35	P<0.001	AI Promotes High-tech Industries Stronger
	Medium and low-tech industries	1.21	P<0.05	The promotion effect is weak
Feature type	Capital-intensive industries	2.03	P<0.01	Capital and AI are more complementary
	Labor-intensive industries	0.87	P=0.08	The effect is not significant (substitution effect exists)

As shown in Table 5, the mechanism is the industries with higher capital intensity, human capital and Research and Development (R&D) investment, and the stronger the growth effect of AI, indicating that AI technology needs to be combined with the quality of factors to play its maximum role. Heterogeneity is that high-tech industries and capital-intensive industries benefit more from AI, while labor-intensive industries are less affected by AI (the growth effect may be offset by technology substitution effect). This experiment effectively controls the industry's inherent differences and time trends through the DID model. The results are tested by multiple robustness tests, which can provide an empirical basis for AI industry policy formulation.

4. Conclusion

Based on the industry panel data from 2003 to 2017, this paper applies the DID model to empirical analysis and finds that the technological innovation of artificial intelligence has a significant positive impact on economic growth. The economic growth rate of the processing group industry with intensive application of artificial intelligence or concentrated patents is significantly higher than that of the control group, and the effect increases with time. From the perspective of industry heterogeneity, the high-tech manufacturing industry, the knowledge-intensive service industry, and the capital-intensive industry benefit more significantly, while the labor-intensive industry has a weak short-term effect. The mechanism is mainly embodied in efficiency improvement and innovation-driven. The conclusion is reliable after robustness test. Further research shows that the synergistic effect of artificial intelligence and research and development investment can amplify the growth effect and has higher marginal effect on capital-intensive industries, which confirms the "capital-technology complementarity" theory. At the same time, the research results of this paper have both consistency and incremental contribution with the mainstream research: at the consensus level, it verifies the positive impact of artificial intelligence on economic growth, the efficiency and innovation driving mechanism and the "capital-technology complementarity" theory; At the incremental level, the characteristics of industry heterogeneity are refined, the dynamic trend of AI effect increasing with time is clarified, the early application stage of AI from 2003 to 2017 is focused to fill the blank of mainstream research samples, and patent data are suggested or long-term effect is underestimated, which provides improvement direction for follow-up research. The whole is the consolidation and expansion of mainstream research, rather than a subversive new view.

In order to amplify the positive driving effect of artificial intelligence on economic growth, efforts should be made from three aspects in the future: first, increase investment in research and development of core technologies of artificial intelligence, focus on supporting key areas such as basic algorithms and chips, enhance the capability of independent technological innovation, and strengthen the driving force for sustained growth; The second is to promote the deep integration of artificial intelligence and industry, formulate differentiated policies based on industry heterogeneity, encourage the exploration of new formats and new models for high-tech industries, reduce the cost of intelligent transformation for traditional industries through subsidies and tax incentives, and at the same time strengthen skills training for practitioners to mitigate skills mismatch; Third, improve the data and patent protection system, optimize the market environment for technological transformation, and promote the transformation of patent achievements into actual productive forces. With the implementation of these measures, it is expected to make up for the shortage of current technologies and uneven benefits to industries, promote the more efficient empowerment of various industries by artificial intelligence, and inject stronger and more lasting momentum into high-quality economic growth.

Reference

[1] Hasudungan A, Sulistiawaty E. McCarthy, John F., Andrew McWilliam, and Gerben Nooteboom. The Paradox of Agrarian Change: Food Security and the Politics of Social Protection in Indonesia. Journal of Global South Studies, 2024, 41(2): 334-336.

[2] Zhou J. Theoretical and practical research on high-quality development of the Chinese economy since the 19th National Congress. Changsha University of Science and Technology, 2022.

[3] Hanson R. Economic Growth Given Machine Intelligence. Technical Report, University of California, Berkeley, 2021.

[4] Autor D H. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives, 2025, 29(3): 3-30.

[5] Huang J. Capital return rate, human capital investment, and income inequality: an extension based on the Galor Zeira model. Business Research, 2020, 25(3): 113-121.

[6] Zhang C, Yuan S, Tang J D. Acemoglu's Contribution to Macroeconomics and Labor Economics. Journal of Hebei University of Economics and Business, 2024, 45(6): 25-35.

[7] Aghion P, et al. Artificial intelligence and economic growth. NBER Working Paper, 2017.

[8] Brynjolfsson E, Hitt L M, Kim H H. Strength in Numbers: How Does Data-driven Decisionmaking Affect Firm Performance? Social Science Electronic Publishing, 2021, 181(9): 3-20.

[9] Chen Z, Gao X, Lei J. Monitoring of wind erosion in the southern Aral Sea using SBAS-InSAR technology. International Soil and Water Conservation Research, 2025, 13(3): 551-563.

[10] Kromann L, Skaksen J R, Sorensen A. Automation, Labor Productivity and Employment—a Cross Country Comparison. CEBR, Copenhagen Business School Working Paper, 2021.

[11] Graetz G, Michaels G. Robots at Work: The Impact on Productivity and Jobs. Centre for Economic Performance, LSE, 2015.

[12] Huang Z. Research on the Impact of Artificial Intelligence on Economic Growth. Sichuan University, 2021.

[13] Yu H F, Ge L Y, Su X C. How Does Tax Innovation Incentive Policy Affect the Structure of Enterprise Human Capital-Based on the Effect of "Capital-Technology Complementarity" of the Policy of R&D Expenses Plus Deduction. Journal of Guangdong University of Finance and Economics, 2023, 38(4): 37-50.