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Artificial Intelligence and Economic Growth in China: An Empirical Analysis Using Vector Autoregression

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Abstract:
With the rapid development of technology, artificial intelligence (AI) has become a key force driving the new round of technological revolution and industrial transformation, profoundly impacting the global economic landscape. This study aims to reveal the dynamic relationship among China's Gross Domestic Product (LNGDP), effective invention patents in high-tech industries (LNNVI), and R&D expenditure in high-tech industries (LNRDE) through empirical analysis, in order to provide valuable references for policymakers to promote high-quality economic development in China. The study adopts the Vector Autoregression (VAR) model to systematically analyze the public data released by the National Bureau of Statistics of China. LNGDP is selected as the indicator of economic growth, LNNVI and LNRDE as the indicators reflecting the development of the AI industry. Statistical methods such as variance decomposition and impulse response function are used to explore the interactions among these variables. The study finds that China's R&D expenditure in high-tech industries increased from 29.213 billion yuan in 2004 to 650.77 billion yuan in 2022, an increase of about 22 times. The number of effective invention patents increased from 4,535 in 2004 to 809,824 in 2022, an increase of about 178 times. There is a significant positive correlation among LNGDP, LNNVI, and LNRDE, indicating that economic growth and the development of high-tech industries are mutually reinforcing. There is a strong positive correlation between R&D investment and the number of effective invention patents, and the increase in R&D investment directly drives the output of innovation results. The impulse response of LNGDP to LNNVI and LNRDE changes over time, showing the long-term cumulative effect of R&D investment and patent output on economic growth. This study reveals the close link between economic growth and high-tech industries, especially the AI industry. Specifically, economic growth promotes innovation activities and R&D investment in high-tech industries, and the increase in R&D investment further drives patent output, which ultimately has a positive impact on economic growth. Furthermore, the study also finds the long-term cumulative effect of R&D investment and patent output on economic growth. Based on these findings, the study proposes policy recommendations, including increasing support for high-tech industries, strengthening intellectual property protection, improving the efficiency of R&D investment conversion, optimizing the industrial structure layout, enhancing talent cultivation and introduction, promoting international science and technology cooperation and exchange, and focusing on long-term effects, to jointly promote China's economic development towards high-quality growth.

Keywords: Artificial Intelligence, Economic Growth, Dynamic Relationship, VAR Model

INTRODUCTION

With the rapid technological progress, artificial intelligence (AI) has become the core driving force leading the global technological revolution and industrial transformation, exerting a widespread and profound impact on the global economic structure. It not only reshapes the operational models of various industries but also promotes the reconstruction of the global economic landscape. In recent years, the Chinese government has attached great importance to the development of AI technology, not only providing strong policy support but also continuously increasing R&D investment to drive technological progress and economic transformation. The rapid development of high-tech industries, especially the breakthroughs in the AI field, have injected new vitality into economic growth. However, the specific impact mechanism of AI on economic growth and their dynamic relationship are not yet fully clear. Understanding and accurately grasping this relationship is of great significance for formulating scientific and reasonable science and technology policies and economic development strategies.

Domestic and foreign scholars have conducted relevant research.

P. Aghion et al. have explored the mechanism of how AI drives economic growth, believing that AI has an important impact on economic growth [1].

Cheng and Chen, based on theoretical and empirical research, have analyzed how AI promotes China's economic growth, believing that AI's promotion of China's economic growth has a clear mechanism [2].

Geng and Wang have analyzed the specific impact path and mechanism of AI on industrial development, believing that AI has an important impact on the path and mechanism of China's industrial development [3].

Wu has analyzed the path and mechanism of intelligent economic development, believing that the development path and mechanism of the intelligent economy driven by AI as the core is of great significance [4].

Wang and Wang, through empirical research, have examined the role mechanism of the AI industry on economic growth, believing that the AI industry has a significant impact on economic growth [5].

Beraja and Yang et al. point out that the success of data-intensive innovations (such as AI enterprises) in China is closely related to government support, and government policies play a critical role in this process [6]. Hong Song, Sheng Sihan, Wang Qian et al. through literature review, point out the current status, hotspots, and future research directions of AI's economic effects, emphasizing its far-reaching impact across multiple fields [7]. Zhao and Li et al. believe that intelligence (AI) significantly enhances the regional industrial competitiveness of China through technological innovation and efficiency improvement [8]. Cai Yuezhou and Chen Nan propose that under the new technological revolution, AI promotes high-quality economic growth and employment, and policy guidance is needed to maximize its benefits [9]. Lin Chen, Chen Xiaoliang, Chen Weize et al. from the perspective of capital structure optimization, believe that AI promotes economic growth and improves residents' consumption [10]. Chen Yanbin, Lin Chen, Chen Xiaoliang et al. point out that AI mitigates the negative impact of population aging on economic growth by increasing production efficiency and complementing the labor force [11].

In summary, domestic and foreign scholars have extensively studied the dynamic relationship between the AI industry and economic growth. The research believes that there is a close connection between AI and economic growth, and AI can promote high-quality economic development through mechanisms such as industrial structure transformation, total factor productivity improvement, and new driving force cultivation. These studies provide important theoretical support and practical basis for in-depth understanding of the role mechanism of AI in driving economic growth.

This study is based on the Vector Autoregression (VAR) model and uses the public data released by the National Bureau of Statistics of China. Through systematic data organization and rigorous model analysis, it reveals the dynamic relationship between China's AI industry and economic growth. Through this research, we hope to provide valuable references for policymakers, thereby promoting high-quality economic development in China.

DATA ORGANIZATION AND VARIABLE SELECTION

Data Organization

The research data of this paper mainly come from the publicly available data of the National Bureau of Statistics of China. According to Figure 1, China's R&D expenditure in high-tech industries increased from 29.213 billion yuan in 2004 to 650.77 billion yuan in 2022, an increase of about 22 times. From 2004 to 2014, this stage experienced relatively stable growth in expenditure, increasing from 29.213 billion yuan to 192.22 billion yuan, with an average annual growth rate of about 22.7%. From 2015 to 2022, this stage saw a significant acceleration in expenditure growth, especially after 2020, with expenditure growth becoming more prominent. It quickly increased from 307.78 billion yuan in 2019 to 650.77 billion yuan in 2022, with an average annual growth rate of about 29.4%. This continuous and rapid growth indicates that the Chinese government's emphasis on technological innovation has been increasing, and it also reflects the efforts made by China in promoting technological progress, with increasing investment in the research field.

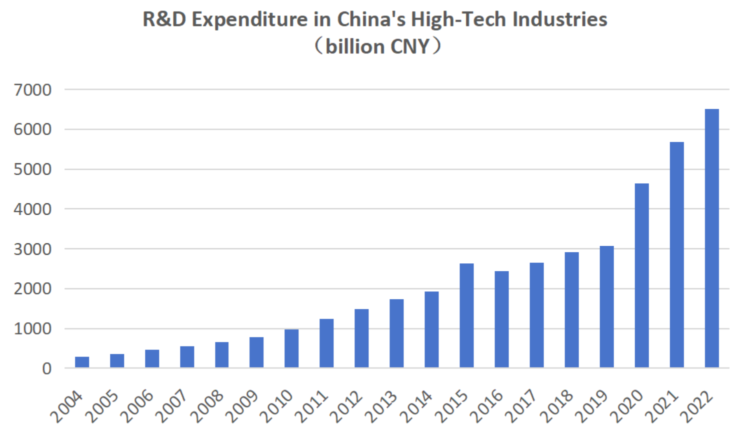

Figure 1. Research and development expenditure in China’s high-tech industry from 2004 to 2022

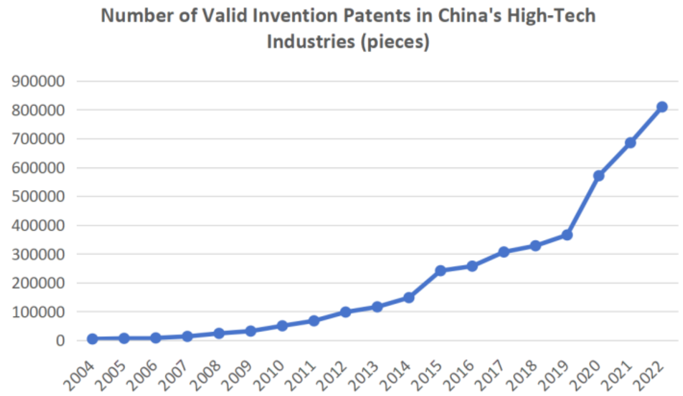

Figure 2. Number of valid invention patents in China's high-tech industry from 2004 to 2022

As shown in Figure 2, the number of valid invention patents increased from 4,535 in 2004 to 809,824 in 2022, an increase of about 178 times. This rapid growth indicates that China's efforts in intellectual property protection have achieved remarkable results, and it also reflects the increasing investment of Chinese enterprises in technological innovation and R&D. From 2004 to 2014, the number of valid invention patents increased from 4,535 to 147,927, with an average annual growth rate of about 40.5%. From 2015 to 2022, the number of valid invention patents continued to grow rapidly. It quickly increased from 365,523 in 2019 to 809,824 in 2022, with an average annual growth rate of about 30.3%. This indicates that with the development of China's economy and the improvement of its technological level, the enthusiasm of enterprises for patent applications has also been continuously increasing.

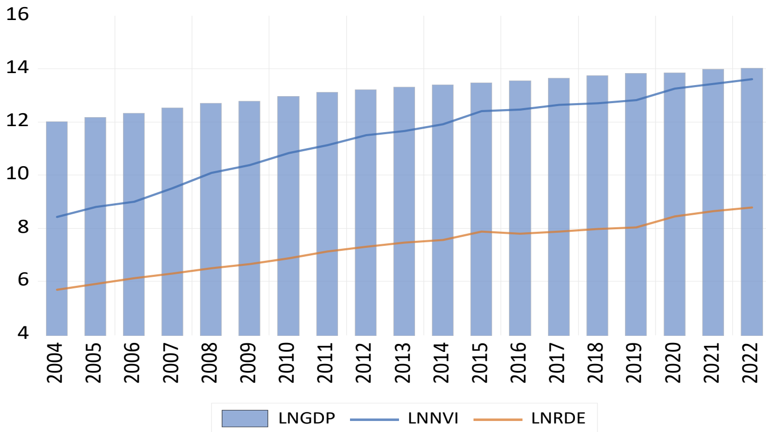

Figure 3. Trends in LNGDP, LNNVI, and LNRDE from 2004 to 2022

Table 1. Descriptive statistics for LNGDP, LNNVI, and LNRDE

Variable Name	LNGDP	LNNVI	LNRDE
Mean	13.16751979	11.39317002	7.309837537
Median	13.29288762	11.66034497	7.458416811
Maximum	14.00176105	13.60457222	8.78074137
Minimum	11.99436471	8.419580363	5.677198909
Std. Dev.	0.625538522	1.637497422	0.931079574
Skewness	-0.437091413	-0.421541422	-0.18575632
Kurtosis	2.010544475	1.939004821	1.95829059
Jarque-Bera	1.380047465	1.453895398	0.968350942
Probability	0.501564166	0.483382169	0.616205066
Sum	250.182876	216.4702303	138.8869132
Sum Sq. Dev.	7.043371974	48.26516052	15.6043651

Variable Selection

This study selects GDP to represent China's Gross Domestic Product as an indicator of economic growth (dependent variable). NVI is selected to represent the number of valid invention patents in China's high-tech industries, and RDE represents the research and development expenditure in China's high-tech industries, both serving as indicators of China's artificial intelligence industry (independent variables). This is done to explore the dynamic relationship between China's artificial intelligence industry and economic growth. To avoid heteroscedasticity, as shown in Figure 3 and Table 1, this study uses LNGDP, LNNVI, and LNRDE to denote the natural logarithms of the respective variables.

According to the correlation coefficient matrix in Table 2, the following analysis can be made: The Pearson correlation coefficient between LNGDP and LNNVI is 0.997, and it is significant at the 1% significance level. This indicates that there is a very strong positive correlation between GDP and the number of valid invention patents in high-tech industries. The Pearson correlation coefficient between LNGDP and LNRDE is 0.991, and it is significant at the 1% significance level. This indicates that there is a very strong positive correlation between GDP and R&D expenditure in high-tech industries. The Pearson correlation coefficient between LNNVI and LNRDE is 0.994, and it is significant at the 1% significance level. This indicates that there is a very strong positive correlation between the number of valid invention patents and R&D expenditure in high-tech industries. From the analysis of the Pearson correlation coefficients, it can be seen that LNGDP, LNNVI, and LNRDE have very strong positive correlations with each other, and the correlations are significant at the 1% significance level.

There is a close relationship between economic growth and the number of invention patents and R&D expenditure in high-tech industries. The rapid economic growth has provided a solid foundation for the development of high-tech industries, and the development of high-tech industries has also promoted further economic growth. There is a very strong positive correlation between R&D expenditure and the number of invention patents in high-tech industries, indicating that the increase in R&D expenditure directly drives the output of innovative results. The government's policy support in promoting economic growth and the development of high-tech industries plays an important role in enhancing the innovation capability and competitiveness of high-tech industries. In the future, how to further improve the conversion efficiency of R&D investment, promote the deep integration of industry, academia, and research, and promote the continuous innovation of high-tech industries are all issues worthy of attention.

Table 2. Pearson correlation coefficients for LNGDP, LNNVI, and LNRDE

Variable Name	LNGDP	LNNVI	LNRDE
LNGDP	1(0.000***)	0.997(0.000***)	0.991(0.000***)
LNNVI	0.997(0.000***)	1(0.000***)	0.994(0.000***)
LNRDE	0.991(0.000***)	0.994(0.000***)	1(0.000***)
Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.			

EMPIRICAL MODEL VERIFICATION

ADF Stationarity Test

To test the stationarity of the time series of LNGDP, LNNVI, and LNRDE, the unit root test method is used first. From Table 3, the following analysis can be made: The ADF-Fisher Chi-square test statistic is 16.82363978, and the corresponding p-value is 0.009953722, which is less than the significance level of 0.05. This indicates that we can reject the null hypothesis "there is a unit root", meaning that these variables are stationary. The ADF-Choi Z-stat test statistic is -1.89713155, and the corresponding p-value is 0.028905289, which is less than the significance level of 0.05. This also indicates that we can reject the null hypothesis "there is a unit root", meaning that these variables are stationary.

Combining the above two test results, the conclusion can be drawn: the three variables LNGDP, LNNVI, and LNRDE are all stationary, and there is no unit root problem. That is to say, the time series data of these variables are stationary and can be directly used for subsequent econometric analysis, without the need for differencing.

Table 3. Unit root test of the variables

Method	Statistic	Prob.**
ADF - Fisher Chi-square	16.82363978	0.009953722
ADF - Choi Z-stat	-1.89713155	0.028905289

VAR Model Identification and Construction

Based on the VAR model comparison results given in Table 4, it can be known that: From the LR test results, the LR statistic reaches the maximum value at a lag of 1, and it is significant at the 5% significance level, which indicates that the optimal choice of lag length is 1. From the FPE (Final Prediction Error) indicator, when the lag length is 1, the FPE indicator reaches the minimum value, further verifying that the lag length of 1 is the optimal choice. From the AIC, SC, and HQ information criteria, when the lag length is 1, these three indicators all reach the minimum values, which also indicates that the choice of a lag length of 1 is the most appropriate.

Based on the above comparison results, the VAR model with a lag of 1 performs best in all information criteria (LR, FPE, AIC, SC, HQ). Therefore, choosing the VAR model with a lag of 1 is the optimal choice, which will help better capture the dynamic relationship between LNGDP, LNNVI, and LNRDE. For this set of time series data, the optimal lag length of the VAR model should be chosen as 1. Therefore, a VAR (1) model can be established as the optimal model by selecting a lag length of 1.

Based on the VAR model parameter estimation results shown in Table 5, the analysis is as follows:

LNGDP equation: The coefficient of LNGDP(-1) is 0.807678623, and it is significant at the 1% significance level, indicating that the previous period LNGDP has a significant positive impact on the current period LNGDP. The coefficients of LNNVI(-1) and LNRDE(-1) are 0.024689088 and 0.04711579, respectively, but both are not significant, indicating that the previous period LNNVI and LNRDE do not have a significant impact on the current period LNGDP.

Table 4. Comparison of VAR models with different lag orders

Lag	LR	FPE	AIC	SC	HQ
0	NA	3.83E-05	-1.657265	-1.512405	-1.649847
1	84.34258*	1.08e-07*	-7.560813*	-6.981372*	-7.531141*
2	6.252914	1.94E-07	-7.130581	-6.116559	-7.078655
3	4.585812	4.41E-07	-6.769883	-5.32128	-6.695703

Table 5. Parameter estimation of var models

Parameter	**LNGDP**	**LNNVI**	**LNRDE**
LNGDP(-1)	0.807678623	1.65759801	0.989477883
	0.169532651	0.584659001	0.490530022
	[4.76415]	[2.83515]	[2.01716]
LNNVI(-1)	0.024689088	0.244655489	-0.342004842
	0.081933608	0.282560446	0.237068755
	[0.30133]	[0.86585]	[-1.44264]
LNRDE(-1)	0.04711579	0.126273849	0.909801408
	0.092175855	0.317882386	0.266703931
	[0.51115]	[0.39723]	[3.41128]
C	2.016191686	-13.86132778	-8.304223125
	1.498553563	5.167988733	4.335952445
	[1.34543]	[-2.68215]	[-1.91520]
R-squared	0.997068131	0.994992744	0.989271669
Adj. R-squared	0.996439873	0.993919761	0.98697274
Sum sq. resids	0.016390963	0.194940937	0.137223646
S.E. equation	0.034216708	0.118001494	0.09900348
F-statistic	1587.03678	927.3141751	430.3186496
Log likelihood	37.47167831	15.18798008	18.3477413
Akaike AIC	-3.719075367	-1.243108898	-1.594193477
Schwarz SC	-3.521214977	-1.045248507	-1.396333087
Mean dependent	13.23269507	11.55836944	7.400539683
S.D. dependent	0.573463082	1.513307437	0.867409001

LNNVI equation: The coefficient of LNGDP(-1) is 1.65759801, and it is significant at the 1% significance level, indicating that the previous period LNGDP has a significant positive impact on the current period LNNVI. The coefficient of LNNVI(-1) is 0.244655489, but it is not significant, indicating that the previous period LNNVI does not have a significant impact on the current period LNNVI. The coefficient of LNRDE(-1) is 0.126273849, but it is also not significant, indicating that the previous period LNRDE does not have a significant impact on the current period LNNVI.

LNRDE equation: The coefficient of LNGDP(-1) is 0.989477883, and it is significant at the 5% significance level, indicating that the previous period LNGDP has a significant positive impact on the current period LNRDE. The coefficient of LNNVI(-1) is -0.342004842, and it is significant at the 10% significance level, indicating that the previous period LNNVI has a significant negative impact on the current period LNRDE. The coefficient of LNRDE(-1) is 0.909801408, and it is significant at the 1% significance level, indicating that the previous period LNRDE has a significant positive impact on the current period LNRDE.

Overall, the lagged term of LNGDP has a strong explanatory power for itself, with an R-squared of 0.997. The lagged term of LNGDP has a strong explanatory power for LNNVI, with an R-squared of 0.995. The lagged terms of LNGDP, LNNVI, and LNRDE have a strong explanatory power for LNRDE, with an R-squared of 0.989.

Based on the model parameter estimation results, the following equations can be established:

$$\begin{aligned} LNGDP &= C(1,1)*LNGDP(-1) + C(1,2)*LNNVI(-1) \\ &+ C(1,3)*LNRDE(-1) + C(1,4) \end{aligned} \tag{1}$$

$$\begin{aligned} LNNVI &= C(2,1)*LNGDP(-1) + C(2,2)*LNNVI(-1) \\ &+ C(2,3)*LNRDE(-1) + C(2,4) \end{aligned} \tag{2}$$

$$\begin{aligned} LNRDE &= C(3,1)*LNGDP(-1) + C(3,2)*LNNVI(-1) \\ &+ C(3,3)*LNRDE(-1) + C(3,4) \end{aligned} \tag{3}$$

Model Stability Test

Table 6 and Figure 4 display the real parts and moduli of the eigenvalues of the AR model. The modulus of the first root is 0.957451782, the modulus of the second root is 0.824248487, and the modulus of the third root is 0.180435251. All these moduli are less than 1, which means that the AR model is stable. The VAR model passes the AR stability test, as all the moduli of the eigenvalues are less than 1, indicating that the model is stable, the time series is stationary, and the parameter estimates are reliable, thus avoiding the issue of spurious regression. There are no complex roots in the model, implying no cyclical fluctuations. Therefore, the corresponding VAR model is stable.

Table 6. Results of AR stationarity test

Root	Modulus
0.957452	**0.957451782**
0.824248	**0.824248487**
0.180435	**0.180435251**

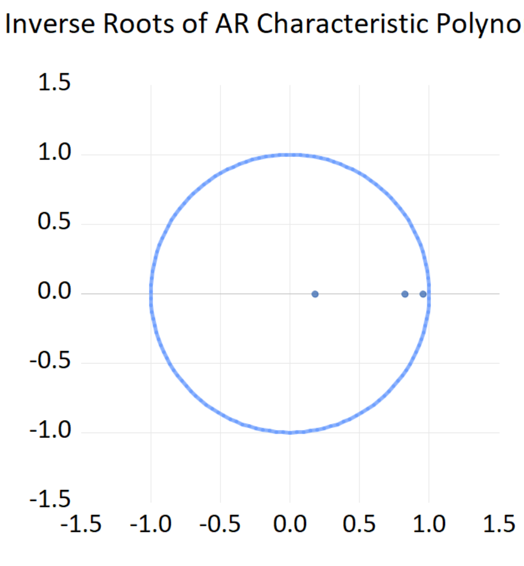

Figure 4. AR unit root stationarity test

Granger Causality Test

Granger causality test is a statistical method to test whether there is a causal relationship between two variables. Table 7 shows the Granger causality test results, and the causality relationships are as follows:

First, LNGDP has an impact on LNNVI. The changes in China's gross domestic product can significantly predict the changes in the number of valid invention patents in the high-tech industry (p = 0.004580367), which passed the 5% significance level. This indicates that economic growth and innovation activities (as measured by the number of valid invention patents) in the high-tech industry have a positive relationship, that is, economic growth may have promoted more innovation activities, thus leading to an increase in the number of invention patents.

Second, LNGDP has an impact on LNRDE. The changes in China's gross domestic product can significantly predict the changes in research and development expenditures in the high-tech industry (p = 0.043678746), which passed the 5% significance level. This means that with economic growth, more funds may be invested in research and development of the high-tech industry, reflecting the support and promotion of economic growth on research and development activities in the high-tech industry. There is a significant Granger causality relationship between China's economic growth and two important indicators of the development of the artificial intelligence industry, the number of valid invention patents and research and development expenditures. These results reveal the positive impact of economic growth on innovation and research and development activities in the high-tech industry, further emphasizing the interactive relationship between economic development and technological innovation.

Based on the test results shown in Table 7, it can be concluded that LNGDP is the Granger cause of LNNVI, and LNGDP is also the Granger cause of LNRDE. However, LNNVI and LNRDE are not the Granger causes of LNGDP. This means that the changes in LNGDP may lead and cause the changes in LNNVI and LNRDE, but the reverse is not true.

Impulse Response Function Analysis

The impulse response function is used to analyze the response of one variable to a shock in another variable. Through analysis, the relationship between variables and their reactions to shocks can be understood. The following is the analysis of the impulse response of LNGDP to its own, LNNVI, and LNRDE shocks, as shown in Figure 5.

The response of LNGDP to its own shock, in the 1st period, the response of LNGDP to its own shock is the largest at 0.034216708, and it gradually decreases over time, and is 0.016177734 by the 10th period. This indicates that the impact of LNGDP on its own shock is greater in the initial period, and then gradually weakens.

Table 7. Granger causality test results

Dependent variable: LNGDP			
Excluded	Chi-sq	df	Prob.
LNNVI	0.090800019	1	0.76316255
LNRDE	0.261275446	1	0.609245257
All	0.862446239	2	0.649713931
Dependent variable: LNNVI			
Excluded	Chi-sq	df	Prob.
LNGDP	8.038095336	1	0.004580367
LNRDE	0.157795243	1	0.691194548
All	8.228981642	2	0.016334255
Dependent variable: LNRDE			
Excluded	Chi-sq	df	Prob.
LNGDP	4.068937292	1	0.043678746
LNNVI	2.081209842	1	0.149121941
All	4.113121131	2	0.127893094

The response of LNGDP to the shock of LNNVI, in the 2nd period, the response of LNGDP to LNNVI is 0.005543749, and then gradually decreases, and is 0.003036574 by the 10th period. This indicates that the response of LNGDP to the shock of LNNVI is relatively small, and gradually weakens over time.

The response of LNGDP to the shock of LNRDE, in the 2nd period, the response of LNGDP to LNRDE is 0.003824333, and then gradually increases, and is 0.014404882 by the 10th period. This indicates that the response of LNGDP to the shock of

LNRDE is relatively small in the initial period, but gradually increases over time.

The response of LNGDP to its own shock is relatively large in the initial period and then gradually weakens; the response to the shock of LNNVI is relatively small and gradually weakens; while the response to the shock of LNRDE is relatively small in the initial period, but gradually increases over time. This indicates that China's gross domestic product (LNGDP) is mainly affected by its own impact in the initial period, but as time goes by, the research and experimental development expenditures of the high-tech industry (LNRDE) have an increasing impact on it.

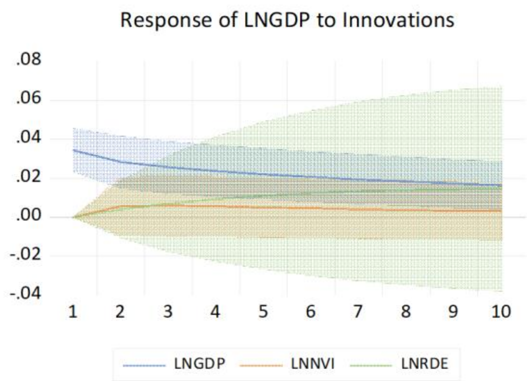

Figure 5. Response of LNGDP to shocks

From Figure 6, we can observe the analysis of the impulse response of LNNVI to LNGDP, LNNVI, and LNRDE.

The response of LNNVI to the shock of LNGDP, in the 1st period, the response of LNNVI to LNGDP is 0.019165689, and then gradually increases, reaching a peak of 0.064608673 in the 3rd period, and then gradually decreases, and is 0.042752028 by the 10th period. This indicates that the response of LNNVI to the shock of LNGDP gradually increases in the initial period, reaches a peak, and then gradually weakens.

The response of LNNVI to its own shock, in the 1st period, the response of LNNVI to its own shock is the largest at 0.116434656, and then quickly decreases, and is 0.008020259 by the 10th period. This indicates that the impact of LNNVI on its own shock is greater in the initial period, and then quickly weakens.

The response of LNNVI to the shock of LNRDE, in the 2nd period, the response of LNNVI to LNRDE is 0.010249499, and then gradually increases, and is 0.038114157 by the 10th period. This indicates that the response of LNNVI to the shock of LNRDE is relatively small in the initial period, but gradually increases over time.

In summary, the response of LNNVI to the shock of LNGDP gradually increases in the initial period, reaches a peak, and then gradually weakens; the response to its own shock is greater in the initial period, and then quickly weakens; while the response to the shock of LNRDE is relatively small in the initial period, but gradually increases over time. This indicates that LNNVI is mainly affected by its own impact in the initial period, but as time changes, LNGDP and LNRDE have an increasing impact on it.

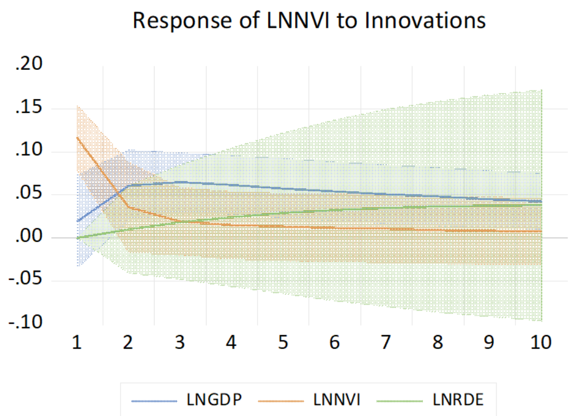

Figure 6. Response of LNNVI to innovations

From Figure 7, the impulse response of LNRDE to LNGDP, LNNVI, and LNRDE can be analyzed.

The response of LNRDE to LNGDP, in the first period, is -0.00203768, then gradually increases, reaching a peak of 0.029957843 in the third period, and then gradually decreases, reaching 0.025375167 in the tenth period. This indicates that the impulse response of LNRDE to LNGDP has a slight negative impact initially, then gradually becomes positive and reaches a peak, and then slightly weakens.

The response of LNRDE to LNNVI, in the first period, is 0.056649449, then rapidly decreases, reaching 0.003142913 in the tenth period. This indicates that the impulse response of LNRDE to LNNVI is relatively large initially, then rapidly weakens.

The response of LNRDE to itself, in the first period, has the maximum value of 0.081168817, then gradually decreases, reaching 0.040114884 in the tenth period. This indicates that the impulse response of LNRDE to itself is relatively large initially, then gradually weakens.

In summary, the impulse response of LNRDE to LNGDP has a slight negative impact initially, then gradually becomes positive and reaches a peak, and then slightly weakens; the impulse response to LNNVI is relatively large initially, then rapidly weakens; and the impulse response to itself is relatively large initially, then gradually weakens. This suggests that LNRDE is mainly influenced by itself initially, but the influence of LNGDP and LNNVI gradually increases over time.

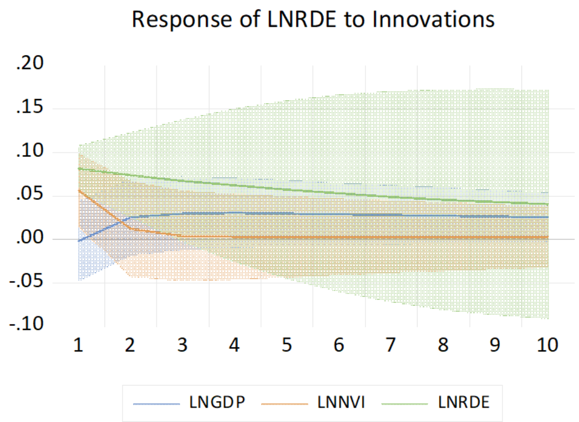

Figure 7. Response of LNRDE to innovations

Variance Decomposition Analysis

Variance decomposition, as a key technical tool, plays an important role in analyzing the internal dynamic mechanism of Vector Autoregression (VAR) models. This technique aims to quantitatively analyze how the specific proportion of changes in one variable within the constructed multivariate interdependent framework can be jointly explained or predicted by other variables in the model.

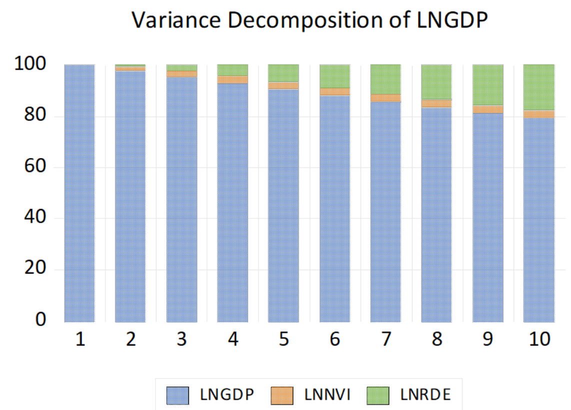

Figure 8. Variance decomposition analysis of LNGDP

Figure 8 present the results of the variance decomposition of LNGDP. The contribution of LNGDP to its own variance: in the 1st period, the contribution of LNGDP to its own variance is 100%, as there is no influence from other variables in the initial period. Over time, the contribution of LNGDP to its own variance gradually decreases, and by the 10th period, it decreases to 79.44895073%. The contribution of LNNVI to the variance of LNGDP: in the 1st period, the contribution of LNNVI to the variance of LNGDP is 0%, as the influence of LNNVI has not yet appeared in the initial period. Over time, the contribution of LNNVI to the variance of LNGDP gradually increases, and by the 10th period, it increases to 2.81402073%. The contribution of LNRDE to the variance of LNGDP: in the 1st period, the contribution of LNRDE to the variance of LNGDP is 0%, as the influence of LNRDE has not yet appeared in the initial period. Over time, the contribution of LNRDE to the variance of LNGDP gradually increases, and by the 10th period, it increases to 17.73702854%.

The variance decomposition results show that, over time, the contribution of LNGDP to its own variance gradually decreases, while the contributions of LNNVI and LNRDE to the variance of LNGDP gradually increase. Particularly, the contribution of LNRDE significantly increases in the long term, indicating that the expenditure on research and experimental development of high-tech industries is gradually strengthening its impact on China's gross domestic product.

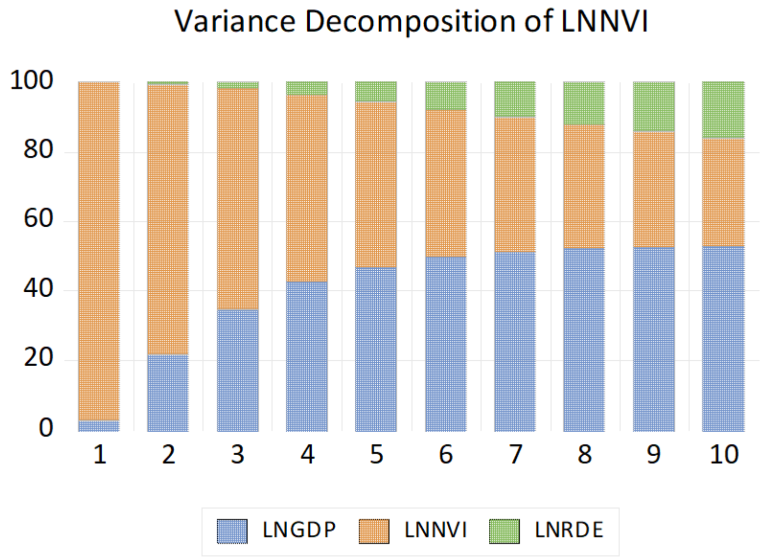

Figure 9. Variance decomposition analysis of LNNVI

From Figure 9, we can see the results of the variance decomposition of LNGDP. The contribution of LNGDP to the variance of LNNVI: in the 1st period, the contribution of LNGDP to the variance of LNNVI is 2.637994439%, indicating that the influence of LNGDP on LNNVI in the initial period is relatively small. Over time, the contribution of LNGDP to the variance of LNNVI gradually increases, and by the 10th period, it increases to 52.63984461%.

The contribution of LNNVI to its own variance: in the 1st period, the contribution of LNNVI to its own variance is 97.36200556%, as there is no influence from other variables in the initial period. Over time, the contribution of LNNVI to its own variance gradually decreases, and by the 10th period, it decreases to 31.21988037%. The contribution of LNRDE to the variance of LNNVI: in the 1st period, the contribution of LNRDE to the variance of LNNVI is 0%, as the influence of LNRDE has not yet appeared in the initial period. Over time, the contribution of LNRDE to the variance of LNNVI gradually increases, and by the 10th period, it increases to 16.14027502%.

The variance decomposition results show that, over time, the contribution of LNNVI to its own variance gradually decreases, while the contributions of LNGDP and LNRDE to the variance of LNNVI gradually increase. Particularly, the contribution of LNGDP significantly increases in the long term, indicating that China's gross domestic product has an increasingly strengthening influence on the effective number of invention patents in high-tech industries. At the same time, the influence of LNRDE is also gradually appearing and strengthening.

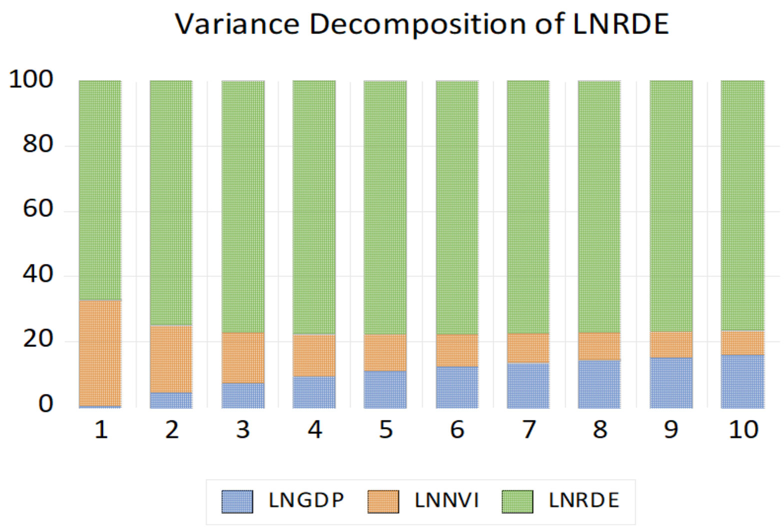

Figure 10. Variance decomposition analysis of LNRDE

From Figure 10, we can know the results of the variance decomposition of LNGDP. The contribution of LNGDP to the variance of LNRDE: in the 1st period, the contribution of LNGDP to the variance of LNRDE is 0.042361489%, indicating that the influence of LNGDP on LNRDE in the initial period is relatively small. Over time, the contribution of LNGDP to the variance of LNRDE gradually increases, and by the 10th period, it increases to 15.68152442%.

The contribution of LNNVI to the variance of LNRDE: in the 1st period, the contribution of LNNVI to the variance of LNRDE is 32.74088806%, indicating that LNNVI has a relatively large influence on LNRDE in the initial period. Over time, the contribution of LNNVI to the variance of LNRDE gradually decreases, and by the 10th period, it decreases to 7.632669719%.

The contribution of LNRDE to its own variance: in the 1st period, the contribution of LNRDE to its own variance is 67.21675045%, as there is no influence from other variables in the initial period. Over time, the contribution of LNRDE to its own variance gradually decreases, and by the 10th period, it decreases to 76.68580586%.

The variance decomposition results show that, over time, the contribution of LNRDE to its own variance gradually decreases, while the contributions of LNGDP and LNNVI to the variance of LNRDE gradually increase. Particularly, the contribution of LNGDP significantly increases in the long term, indicating that China's gross domestic product has an increasingly strengthening influence on the expenditure on research and experimental development of high-tech industries. At the same time, the influence of LNNVI has weakened in the long term, but it still has a certain impact.

CONCLUSION AND RECOMMENDATIONS

Research Conclusion

This paper empirically explores the dynamic relationships between China's Gross Domestic Product (LNGDP), the number of effective invention patents in high-tech industries (LNNVI), and research and development expenditures in high-tech industries (LNRDE). The study finds that:

There is a close connection between high-tech industries and economic growth. The study shows that there is a significant positive correlation among LNGDP, LNNVI, and LNRDE. This correlation is not only reflected between LNGDP and LNNVI but also between LNGDP and LNRDE, as well as between LNNVI and LNRDE. This indicates that economic growth and the development of high-tech industries are complementary; economic growth provides the material foundation for the development of high-tech industries, while the development of high-tech industries further promotes economic growth.

Economic growth promotes high-tech industries. The Granger causality test results show that LNGDP is the Granger cause of LNNVI and LNRDE, but not vice versa. This indicates that the growth of China's GDP can significantly predict changes in the number of effective invention patents and R&D expenditures in high-tech industries, implying that economic growth promotes innovation activities and R&D investment in high-tech industries. This finding underscores the importance of economic growth in driving technological innovation and the development of high-tech industries.

There is a positive relationship between R&D investment and patent output. There is a very strong positive correlation between research and development expenditures in high-tech industries and the number of effective invention patents, indicating that increased R&D investment directly drives the output of innovative results. This result confirms the critical role of R&D investment in enhancing the innovation capability of high-tech industries and provides a basis for the government to formulate relevant policies.

The impact of R&D investment and patent output on economic growth is gradually increasing. The variance decomposition results show that over time, the contribution of LNGDP to the variance of LNNVI and LNRDE gradually increases, especially the contribution of LNRDE. This indicates that the impact of R&D investment and patent output in high-tech industries on China's GDP is gradually increasing, demonstrating the growing contribution of high-tech industries to economic growth.

The long-term effects of R&D investment and patent output. The impulse response function analysis shows that the impulse response of LNGDP to LNNVI and LNRDE changes over time. The impulse response of LNGDP to LNNVI gradually weakens, while the impulse response to LNRDE gradually strengthens. This reflects that the R&D investment and patent output of high-tech industries have a long-term cumulative effect on economic growth.

Policy Recommendations

Based on the research findings, we can propose policy recommendations to better leverage the role of the artificial intelligence industry in promoting stable economic growth and sustainable development, as follows:

(1) Increase support for high-tech industries. Given the important contribution of high-tech industries to economic growth, the government should further increase fiscal and policy support for the artificial intelligence industry. Specific measures include but are not limited to establishing special funds to support R&D activities of high-tech enterprises, providing tax incentives to alleviate the burden on enterprises, and establishing more comprehensive financing channels to help start-ups and SMEs obtain funding support.

(2) Strengthen intellectual property protection. Given the significant positive correlation between the number of effective invention patents and R&D investment, the government should strengthen the intellectual property protection system, including but not limited to improving laws and regulations, enhancing law enforcement, and providing more convenient patent application processes. This not only protects the legitimate rights and interests of innovators, but also encourages more AI companies to invest in technological innovation and product R&D.

(3) Improve the efficiency of R&D investment conversion. To better utilize limited R&D resources, the government and enterprises need to work together to improve the efficiency of R&D investment conversion. On the one hand, by establishing industry-university-research cooperation platforms, promoting collaboration between universities, research institutions, and enterprises, and accelerating the commercialization of scientific and technological achievements; on the other hand, encouraging enterprises to establish internal innovation incentive mechanisms to enhance employee participation in R&D activities.

(4) Optimize the industrial structure layout. Considering the mutual promotion between economic growth and high-tech industries, the government should rationally plan and guide the adjustment and upgrading of the AI industry structure. Focus on supporting high-tech fields with high growth potential and international competitiveness, such as artificial intelligence, biotechnology, and new energy, to promote the entire economic system to move to a higher level.

(5) Strengthen talent cultivation and introduction. The development of high-tech industries is inseparable from a high-quality talent team. Therefore, the government and enterprises need to increase investment in AI industry talent training and introduction. Establish a multi-level talent cultivation system, including basic education, vocational education, and lifelong education, to meet the talent demand at different levels. At the same time, adopt more open talent policies to attract high-end overseas talents to start businesses or work in China.

(6) Promote international scientific and technological cooperation and exchange in AI. In the context of globalization, strengthening cooperation with other countries and regions in high-tech fields is particularly important. The government can actively participate in international scientific and technological exchange and cooperation projects, build international cooperation platforms for enterprises, promote technology transfer and resource sharing, and enhance the international competitiveness of domestic high-tech industries.

(7) Pay attention to the cumulative long-term effects. Given the long-term cumulative effects of R&D investment and patent

output on economic growth, the government and enterprises should have a long-term strategic vision. Not only focus on short-term economic benefits, but also emphasize long-term sustainable development, continuously carry out AI technological innovation and industrial upgrading, and ensure stable economic growth. As the leader of macroeconomic regulation and control, the government should play a guiding role by formulating a series of forward-looking science and technology policies and development plans, and encourage enterprises to increase R&D investment, especially in the exploration of key core technologies and frontier technology fields.

Through the empirical analysis of the VAR model, the dynamic relationship between LNGDP, LNNVI, and LNRDE has been studied. The research finds that there is a significant positive correlation between LNGDP, LNNVI, and LNRDE, indicating that economic growth and high-tech industry development are mutually reinforcing. LNGDP is the Granger cause of LNNVI and LNRDE, showing that economic growth promotes innovation activities and R&D investment in high-tech industries. In addition, R&D investment and patent output are positively correlated, and their impact on economic growth gradually strengthens over time, with long-term cumulative effects. It is recommended to strengthen support for high-tech industries, enhance intellectual property protection, improve the efficiency of R&D investment conversion, optimize the industrial structure layout, strengthen talent cultivation and introduction, promote international scientific and technological cooperation and exchange, and focus on long-term effects, in order to jointly promote China's economy to move towards high-quality development.

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REFERENCES

[1] Aghion, P.; Jones, B.F.; Jones, C.I. Artificial Intelligence and Economic Growth. In The Economics of Artificial Intelligence; Agrawal, A., Gans, J., Goldfarb, A., Eds.; University of Chicago Press: Chicago, IL, USA, 2019; 237–282.

[2] Cheng, C.P.; Chen, Z. The Mechanism of Artificial Intelligence Promoting China's Economic Growth: Based on Theoretical and Empirical Research. Econ. Issues 2021, 506 (10), 8–17.

[3] Geng, Z.H.; Wang, W.X. Research on the Path and Mechanism of Artificial Intelligence Affecting Industrial Development in China. Ind. Technol. Econ. 2022, 41 (02), 100–106.

[4] Wu, H.B. Research on the Development Path and Mechanism of Smart Economy Driven by Artificial Intelligence as the Core. Reform Strategy 2020, 36 (07), 50–57.

[5] Wang, J.; Wang, L.S. The Mechanism and Empirical Test of the Impact of Artificial Intelligence Industry on Economic Growth. J. Shandong Univ. Financ. Econ. 2019, 31 (06), 54–63.

[6] Beraja, M.; Yang, D. State Support and Data-Intensive Innovation: Evidence from AI Firms in China. Journal of Technology Innovation, 2021, 33(4), 67-85.

[7] Hong, S.; Sheng, S.; Wang, Q., et al. A Comprehensive Review of Artificial Intelligence's Economic Effects: Trends, Hotspots, and Future Directions. Science and Technology Management Research, 2022, 42(3), 45-52.

[8] Zhao, L.; Li, X., et al. The Impact of Intelligentization on Regional Industrial Competitiveness: Evidence from China. Management Review, 2021, 33(9), 112-125.

[9] Cai, Y.; Chen, N. AI-Driven High-Quality Economic Growth and Employment in the New Technological Revolution. Economic Perspectives, 2022, 45(2), 78-92.

[10] Lin, C.; Chen, X.; Chen, W., et al. Artificial Intelligence, Capital Structure, and Economic Growth: An Empirical Analysis. Financial Research, 2021, 38(7), 56-70.

[11] Chen, Y.; Lin, C.; Chen, X., et al. Artificial Intelligence and Population Aging: Mitigating Economic Growth Challenges. Population Research, 2022, 46(4), 89-105.