Study on the Influence of Artificial Intelligence in Advancing Rural Industrial Revitalization

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Abstract: As a key technology driving the latest wave of technological innovation and industrial transformation, whether artificial intelligence can become an important means to achieve rural industrial revitalization is worth further research. The results showed that: (1) artificial intelligence has a significant positive promoting effect on the revitalization of rural industries in China, and (2) compared to the central and western regions, the promoting effect of artificial intelligence on rural industry revitalization is more significant in the eastern region. In addition, in areas with a high degree of population aging, the demand and impact of artificial intelligence technology in rural industrial revitalization are more urgent and significant. (3) Agricultural technological innovation, industrial structure rationalization, and labor productivity serve as mediating factors in the influence of artificial intelligence on rural industrial revitalization. Based on this, it is necessary to pay attention to the differences in the empowerment effects of artificial intelligence, fully leverage the 'leading goose' effect of artificial intelligence, and accelerate the effective connection between artificial intelligence and rural industrial revitalization.

Keywords: Artificial Intelligence; Rural Industrial Revitalization; Double Fixed Effects Model; Panel Threshold Model

1. Introduction

The Guiding Opinions on Promoting Rural Industrial Revitalization mention that rural revitalization is a comprehensive revitalization of industries, talents, culture, ecology, and organizations, among which the most important, fundamental, and crucial is industrial revitalization. Industrial revitalization is not only the only way to achieve rural revitalization, but also the prerequisite for solving all rural problems [1]. Therefore, in order to consolidate the achievements of poverty alleviation and ensure the effectiveness of rural revitalization policies in the new era, it is necessary to attach great importance to and promote the development of rural industries [2]. Doing a good job in the revitalization of rural industries is of great significance for promoting the growth of rural economy, improving farmers' income level, improving rural economic structure, realizing diversified development of rural economy, and ultimately achieving common prosperity for all people.

The revitalization of rural industries cannot be achieved without artificial intelligence technology, which is a representative technology of the Fourth Industrial Revolution [3]. Artificial intelligence can leverage its disruptive technological advantages such as unprecedented automation processing, intelligent interaction, and cross domain applications to comprehensively reduce production, operation, management, and governance costs while improving production, operation, service, and resource utilization efficiency, promoting technological upgrading and industrial structure optimization of rural industries. The release of the "Action Plan for Digital Rural Development (2022-2025)" clearly proposes the "Smart Agriculture Innovation and Development Action", aiming to accelerate the development of smart agriculture [4]. The accelerated integration and penetration of artificial intelligence and agricultural and rural development not only marks a new stage of intelligent development in China's agriculture, but also provides new opportunities and impetus for the revitalization of rural industries. Given this, it is necessary to systematically analyze the impact and utility of artificial intelligence on rural industrial revitalization.

2. Study Design

2.1 Data Sources

Conduct research on the impact of artificial intelligence on rural industrial revitalization, and use linear interpolation to handle some missing values. The original data of each variable are from China Agricultural Statistics, China Labor Statistics Yearbook, China Health Statistics Yearbook, and the China National Intellectual Property Administration.

2.2 Selection of Variables

2.2.1 Outcome variable

For rural industrial revitalization, this study employs the entropy weight method to objectively assign weights and calculate a comprehensive index for each province. The construction of an indicator system for rural industrial revitalization should be based on a scientific understanding of the basic connotations and evaluation indicators of rural industrial revitalization, as well as relevant theories and existing research. This article combines the strategic connotation of building a strong agricultural country and, based on the research of Zhang Ting. (2018) [5], constructs an evaluation indicator system according to the definition of rural industrial revitalization by Xu Xue and Wang Yongyu [6]. The detailed evaluation index system is presented in Table 1.

Table 1. Evaluation Index System for the Level of Rural Industrial Revitalization

Primary Indicator	Secondary Indicators	Indicator Description	Attribute	Weight
Rural agricultural development	Comprehensive production capacity of agricultural products	(Grain Production+Oil Production)/Rural Population	+	0.0557
	Development level of agriculture, forestry, animal husbandry and fishery service industry	Output value of agricultural, forestry, livestock, and fishery services/total agricultural output value	+	0.0350
	Total power of agricultural machinery	Application volume of agricultural invention patents	+	0.1374
		Rural broadband access users	+	0.0913
		Total power of agricultural machinery	+	0.0628
Green development of industries	Green Agriculture	Water saving irrigation coverage rate	+	0.0390
		Average fertilizer application per mu	-	0.0088
		Average pesticide application per mu	-	0.0088
	Development level of leisure agriculture	Leisure agriculture revenue/total agricultural output value	+	0.0916
Modernization and Development of Rural Industries	Proportion of non-agricultural income in rural areas	Rural residents' wage income/net income	+	0.0227
	Multi functional industrial system	Total retail sales of rural consumer goods	+	0.0801
		Proportion of net operating income to per capita income	+	0.0167
		Fixed assets investment value of rural households in the tertiary industry	+	0.0571
	Industry related measures	Per capita number of township cultural stations	+	0.0183
		Rural hydropower station	+	0.1447
		Rural electricity consumption	+	0.1299

2.2.2 Independent variable

Artificial Intelligence (AI). This article closely follows the "Guidelines for the Construction of the National New Generation Artificial Intelligence Standard System" issued by five departments including the Ministry of Science and Technology, the Ministry of Industry and Information Technology, and others. Drawing on the research of Yang Xianming and Wang Zhige, Sun Zao and Hou Yulin [7,8]. The entropy weight method is adopted to objectively weight and comprehensively measure the development level of artificial intelligence at the provincial level. The specific evaluation index system is shown in Table 2.

2.2.3 Mediating variables and threshold variables

The mediating variables of this study are as follows: (1) Agricultural Science and Technology Innovation Level (Ati): This study selects the number of agricultural patent authorizations in each region to measure this variable [9]. (2) Rationalization of Industrial Structure (Ris): To capture the quality of inter-industry aggregation, this article employs the Theil index as a measurement indicato [10]. (3) Labor productivity (Lor) is expressed by multiplying the number of employed individuals in each region by the average years of education per person. The threshold variables include farmers' education level (edu) and the regional economic development level (gdp).

Table 2. Evaluation Index System for the Development Level of Artificial Intelligence

Primary Indicator	Secondary Indicators	Indicator Description	Attribute	Weight
Artificial Intelligence Infrastructure Construction	Artificial intelligence talent reserve	The proportion of employment in the information transmission, software, and information technology service industries to the total employment in urban units	+	0.1510
	Investment in Artificial Intelligence Infrastructure	Proportion of fixed assets investment in information transmission, software and information technology service industry in fixed assets investment of the whole society	+	0.0574
Artificial Intelligence Output and Services	Artificial intelligence material output	Software business revenue	+	0.3081
	Artificial intelligence knowledge output	Number of patent applications for artificial intelligence	+	0.3231
	Information reception capability	Internet broadband access port	+	0.1006
	Network transmission capability	Length of optical cable line	+	0.0599

2.2.4 Control variables

In order to minimize the influence of other factors on the empirical results, this article further controlled for the following variable: financial development level (FCE), measured by the ratio of the sum of deposits and loans of banking and financial institutions to GDP. The elderly dependency ratio (old) is the numerical representation of the ratio of non working age elderly population to working age population in the total population of each province and city. Child dependency ratio refers to the proportion of the population aged 0-14 to the working age population aged 15-64. The proportion of rural residents' consumption expenditure (expense) is expressed as the ratio of per capita consumption expenditure of rural residents to per capita regional GDP. The degree of openness to the outside world (ope) is represented by the ratio of total import and export trade to GDP. The Theil index is used to measure the income disparity between urban and rural residents. The level of economic development (GDP) is expressed as the logarithm of per capita regional GDP for each province, autonomous region, and municipality.

2.3 Model Construction

This study uses panel data from 30 provinces in China from 2013 to 2022 to empirically analyze the impact of digital technology on industrial digitization. For this purpose, the following econometric models were constructed:

$$Rural_{it} = \alpha_0 + \beta_1 AI_{it} + \beta_2 fce_{it} + \beta_3 old_{it} + \beta_4 child_{it} + \beta_5 expe_{it} + \beta_6 ope_{it} + \beta_7 theil_{it} + \beta_8 gdp_{it} + \varepsilon_{it} + \mu_i + \upsilon_t \tag{1}$$

In this context, "i" and "t" denote regions and time periods, respectively. "Rural" refers to the dependent variable representing rural industrial revitalization.; AI represents the core explanatory variable of artificial intelligence level. fce (financial development level), old (dependency ratio of the elderly population), child (dependency ratio of the child population), expe (the proportion of rural residents' consumption expenditure), ope (degree of openness to the outside world), theil (Theil index), gdp (economic development level); ε , μ_i , υ_t represent the stochastic error term, individual fixed - effect, and time fixed - effect respectively.

Referring to the research method of Jiangchuan (2022), a benchmark regression model was constructed as shown in equation (2) [11]. To explore the mechanism through which artificial intelligence affects rural industrial development and renewal from three aspects: agricultural technology innovation level, rationalization of industrial structure, and labor productivity, and construct a model:

$$Mit = \alpha 0 + \alpha 1 \text{AIit} + \alpha 2 X\text{it} + \varepsilon\text{it} + \mu i + \upsilon \text{t} \quad (2)$$

In (2), the levels of agricultural technological innovation, rationalization of industrial structure, and labor productivity are listed in order.

3. Measured Results and Conversation

3.1 Analysis of Baseline Estimation Results

Based on model (1), the estimation incorporates double fixed effects. To minimize bias from omitted variables, control variables are gradually introduced in the double fixed-effects regression, following the "general to specific" modeling approach. The empirical results in Table 3 lead to the following conclusions: In column (1), where no control variables are included, the estimated coefficient of artificial intelligence (AI) is significantly positive. In columns (2) to (8), as control variables are progressively added, the estimated AI coefficients remain significantly positive with minimal fluctuation, confirming the robustness of the regression results. This indicates a strong positive correlation between artificial intelligence and rural industrial revitalization, demonstrating AI's significant role in driving rural industrial development. Specifically, a 1-unit increase in AI leads to an 11.9% rise in rural industrial revitalization. These findings support research hypothesis 1, proving that artificial intelligence positively contributes to rural industrial revitalization.

3.2 Robustness Checks and Endogeneity Tests

3.2.1 Eliminate extreme values

To mitigate the potential influence of extreme values on the regression outcomes, tail trimming was applied to the top and bottom 1% of extreme values in the sample data. Following this, a regression was performed using the truncated variable values based on model (1), with the results presented in column a of Table 4. The coefficient for artificial intelligence is 0.128, suggesting that the positive impact of artificial intelligence on rural industrial revitalization is robust, thus enhancing the reliability of the regression findings.

3.2.2 Divide into different time periods and sample regression

The original sample period is from 2013 to 2022. This article divides the time period into 2013-2017 and 2018-2022 for sub sample regression to ensure the robustness of the regression results. The regression results are presented in columns c and d of Table 4, where the coefficients of artificial intelligence remain positive and significant at the 5% level. This aligns with the findings of the benchmark regression, further confirming the robustness of the results.

Table 3. Results Benchmark Regression Results (Gradually Introducing Control Variables)

	Rural							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI	0.155** (2.72)	0.146** (2.58)	0.139*** (2.88)	0.151*** (3.12)	0.151*** (3.17)	0.133** (2.52)	0.139** (2.43)	0.119** (2.14)
fce		-0.021*** (-3.69)	-0.026*** (-4.82)	-0.023*** (-4.45)	-0.023*** (-4.29)	-0.205*** (-4.86)	-0.026*** (-4.21)	-0.026*** (-4.90)
old			0.0032** (2.07)	0.0029** (2.02)	0.0029** (2.02)	0.0025 (1.59)	0.0025 (1.62)	0.0028** (1.98)
child				0.196*** (2.91)	0.192*** (2.85)	0.1940*** (2.83)	0.194*** (2.86)	0.149**(2.15)
expe					0.000042 (1.65)	0.00005** (2.27)	0.00005** (2.29)	0.00007*** (3.41)
theil						0.3450 (0.92)	0.343 (0.94)	0.897** (2.10)
ope							0.056 (0.53)	0.389** (2.27)
gdp								0.084*** (2.92)

Constant	0.156*** (29.60)	0.216*** (14.41)	0.195*** (9.49)	0.139*** (5.25)	0.135*** (5.00)	0.1081**(2.59)	0.1039** (2.59)	-0.883** (-2.64)
Province/year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.7535	0.7711	0.7833	0.7955	0.7973	0.7996	0.8002	0.8235

Note: The statistics inside parentheses indicate t-values adjusted using clustered robust standard errors. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively; the same applies hereafter.

Table 4. Robust Test

	Rural			
	a	b	c	d
AI	0.128* (1.78)	0.326*** (4.45)	0 .074** (2.55)	0.123** (2.15)
Fsa				-0.035*** (-2.86)
Pir				0.236** (2.49)
Constant	-0.8962*** (-2.66)	0.145*** (4.71)	0.157*** (4.20)	-2.36** (-2.67)
Contral	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R-squared	0.8216	0.7495	0.5664	0.8246
N	300	150	150	300

3.2.3 Increase control variables

By adding some control variables, the robustness of the regression results can be demonstrated. On the basis of the original control variables, this article adds two control variables, namely fiscal support for agriculture and per capita income of rural residents, to conduct a double fixed effects test. The regression results are shown in column d of Table 4, and the coefficient of artificial intelligence is still positive and significant at the 1% level. The credibility of the positive promotion effect of artificial intelligence on rural industrial revitalization has been increased

3.2.4 Quantile regression

This article uses two-stage least squares (2SLS) method to solve the endogeneity problem caused by reverse causality. This article uses the following two instrumental variables: (1) the average value of artificial intelligence in provinces other than our province in China. On the one hand, there is a correlation between the development of artificial intelligence in neighboring provinces. On the other hand, at present, artificial intelligence is mainly in the weak artificial intelligence stage, so artificial intelligence in provinces other than our province will not affect the development of rural industries in our province. Based on this, the instrumental variable meets the requirements of correlation and exogeneity the explanatory variable of artificial intelligence lags behind by one period. The development of rural industries at present does not influence artificial intelligence development from the previous year. Instead, the impact of artificial intelligence from the previous year on rural industries occurs indirectly through its continued development in the current year. Based on this, the instrumental variable meets the requirements of correlation and exogeneity.

3.2.5 Introducing instrumental variables

Endogeneity is an unavoidable concern in economic research. Considering the framework of this investigation, the swift expansion of industrial digitalization is inherently connected to the innovation and advancement of digital technology. Conversely, the progression of digital technology is closely tied to the dynamics of industrial digitalization, suggesting an inherent causal relationship between the two. Moreover, many factors influence industrial digitalization, and the control variables included in the study may omit certain relevant variables. Given these potential issues of inherent causality and omitted variables, this study addresses endogeneity by introducing instrumental variables.

3.3 Heterogeneity Analysis

3.3.1 Regression by regional

This article divides the 30 provinces in the sample into 11 provinces located in the east and 19 provinces located in the central and western regions according to empirical methods. The sample regression further explores the regional heterogeneity of the impact of artificial intelligence on rural industrial revitalization. In the eastern region, artificial intelligence has a significant positive effect on rural industrial revitalization. However, compared to the eastern region, its impact in the central and western regions is not statistically significant. Perhaps due to the strong industrial foundation and advantageous location in the eastern region, the promotion of artificial intelligence has become more rapid.

3.3.2 Analysis According to the degree of aging

The population is categorized into high and low groups based on the annual average aging level of each province to examine the varying effects of artificial intelligence on rural industrial revitalization under different aging conditions. The grouped regression results in Table 5 indicate that artificial intelligence has a significantly positive impact on rural industrial revitalization across different aging levels. The difference is that the coefficient of artificial intelligence in low aging areas is 0.065, which is lower than that in high aging areas, which is 0.145. This indicates that in areas with a high degree of population aging, the demand and impact of artificial intelligence technology in rural industrial revitalization are more urgent and significant due to factors such as labor shortage and increased service demand.

3.3.3 Heterogeneity in economic development levels

To examine the igital innovation's impact on industrial digitalization in cities with varying levels of economic development, this study draws on Wang Yongqin et al.'s classification criteria for urban economic development levels. It uses per capita GDP as an indicator to measure the stage of economic progress. and divides the sample into two groups: high economic development and low economic development. Regression analysis is then conducted for each group.

3.4 Mediation Mechanism Test

Although the previous analysis has confirmed that artificial intelligence has promoted the development of rural industries, its specific path is still unclear. Considering the varying stages of development of artificial intelligence, this study employs a mediation model to investigate how artificial intelligence influences industrial digitization through three distinct pathways: "agricultural technological innovation," "industrial structure optimization," and "labor productivity."

3.5 Threshold Effect Test

Due to the varying levels of education and economic development among farmers in different regions, artificial intelligence may have a non-linear impact on the revitalization of rural industries. Therefore, it is necessary to conduct threshold effect tests on farmers' education levels and regional economic development levels. This article uses a panel threshold model to construct two threshold models with farmers' education level (edu) and regional economic development level (GDP) as threshold variables, as shown in formulas (3) and (4):

$$Rural_{it} = \alpha_0 + \beta_1 AI_{it}I(\text{edu} \le \lambda) + \beta_2 AI_{it}I(\text{edu} > \lambda) + \beta_3 fce_{it} + \beta_4 old_{it} + \beta_5 child_{it} + \beta_5 child_{it} + \beta_4 old_{it} + \beta_5 child_{it} + \beta_6 expe_{it} + \beta_7 ope_{it} + \beta_8 theil_{it} + \beta_9 gdp_{it} + \varepsilon_{it} + \mu_i + \upsilon_t \quad (3)$$

$$Rural_{it} = \alpha_0 + \beta_1 AI_{it}I(\text{gdp} \le \lambda) + \beta_2 AI_{it}I(\text{gdp} > \lambda) + \beta_3 fce_{it} + \beta_4 old_{it} + \beta_5 child_{it} + \beta_5 child_{it} + \beta_4 old_{it} + \beta_5 child_{it} + \beta_6 expe_{it} + \beta_7 ope_{it} + \beta_8 theil_{it} + \beta_9 gdp_{it} + \varepsilon_{it} + \mu_i + \upsilon_t \quad (4)$$

Table 5. Results Benchmark Regression Results (Gradually Introducing Control Variables)

	Rural	
edu≦8.0683	0.2203*** (5.65)	
edu>8.0683	0.1349*** (3.45)	
gd≦9.2990		0.1608***(2.84)
gdp>9.2990		0.1211**(2.54)

fce	-0.0157***(-3.62)	-0.0188***(-4.38)
old	0.0022**(2.67)	0.0025**(2.52)
child	0.1474**(2.43)	0.1536**(2.63)
expe	0.000056***(3.08)	0.000058***(2.94)
theil	0.8118***(2.97)	0.8463***(2.81)
ope	0.3932***(4.12)	0.4023***(3.97)
gdp	0.0882***(6.08)	0.0944***(5.61)
Constant	-0.9392***(-5.15)	-1.0027***(-4.84)
R-squared	0.8251	0.8169
N	300	300
BS	5000	5000

As illustrated in Table 5, when the education threshold is ≤8.0683, the estimated coefficient of artificial intelligence is 0.2203, showing a significant positive correlation at the 1% confidence level. That is, for every 1% increase in artificial intelligence, the level of rural industrial revitalization will increase by 22.03%. When the threshold value of education (edu) exceeds 8.0683, the estimated coefficient of artificial intelligence is 0.1349, demonstrating a significant positive correlation at the 1% confidence level. That is, for every 1% increase in artificial intelligence, the level of rural industrial revitalization will increase by 13.49%. This significant positive promotion effect has a significant decrease compared to others. Perhaps because in the first stage, farmers with higher levels of education may be more likely to understand and apply artificial intelligence technology. They may have stronger technological adaptability and learning ability, thus adopting new technologies faster and integrating them into their industries. As the stage progresses, farmers with lower education levels may need longer time to understand and adapt to new technologies, leading to a weakened promotion effect in the second stage. When the threshold GDP is≤9.299, the estimated coefficient of artificial intelligence is 0.1608, which is significantly positively correlated at a 1% confidence level. That is, for every 1% increase in artificial intelligence, the level of rural industrial revitalization will increase by 16.08%. When the threshold value gdp>9.299, the estimated coefficient of artificial intelligence is 0.1211, which is significantly positively correlated at a 5% confidence level. That is, for every 1% increase in artificial intelligence, the level of rural industrial revitalization will increase by 12.11%. This significant positive promotion effect is relatively reduced. Perhaps it is mainly due to the adoption of artificial intelligence technology in economically developed regions, as these areas have more funds and resources to invest in new technologies. These regions may have better infrastructure, richer talent resources, and more capital, which is conducive to the implementation of artificial intelligence technology. However, as the stage progresses, relatively impoverished areas may be limited by resources, making it difficult to effectively apply artificial intelligence technology, resulting in a weakened promotion effect of the second stage.

4. Conclusion

This article conducts a thorough analysis of the theoretical mechanisms through which artificial intelligence influences rural industrial revitalization. Using provincial panel data from 30 Chinese provinces spanning 2013 to 2022, it develops a comprehensive evaluation index system for artificial intelligence and rural industrial revitalization from multiple perspectives. This study conducts a comprehensive assessment of the development levels of artificial intelligence and rural industrial revitalization. It employs a dual fixed-effects model and a threshold panel model to empirically analyze their relationship. The main findings are as follows: First, artificial intelligence significantly contributes to the revitalization of rural industries in China, playing a crucial role in advancing their development. Secondly, due to regional disparities in the development of artificial intelligence, its impact on rural industrial revitalization exhibits significant heterogeneity. Compared to the central and western regions, artificial intelligence plays a more prominent role in driving rural industrial revitalization in the eastern region. In addition, in areas with a high degree of population aging, due to factors such as labor shortage and increased demand for services, the demand and impact of artificial intelligence technology in rural industrial revitalization are more urgent and significant. Thirdly, there is a mediating effect of agricultural technological innovation level, rationalization of industrial structure, and labor productivity in the process of artificial intelligence affecting rural industrial revitalization. Fourthly, further research has shown that artificial intelligence has a single threshold effect on rural industrial revitalization based on the education level of farmers and the level of regional economic development. After crossing the threshold, the role of artificial intelligence in promoting rural industrial revitalization decreases.

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