



Analysis of the Path for Wanzhou District to Empower Manufacturing Upgrades with 'Artificial Intelligence'

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Abstract. This paper takes the manufacturing industry in Wanzhou District, Chongqing Municipality as the research object, and uses a combination of grey relational analysis and benchmark regression models to establish a two-stage method and build an empirical analysis model. Based on this, three paths are proposed: increasing investment in intelligent technological transformation, expanding industrial AI applications, increasing R&D investment and making good use of subsidies, while improving information infrastructure, narrowing the urban-rural gap, and coordinating multiple parties to build a local 'artificial intelligence + manufacturing' upgrade system. peed of both single-loop and multi-loop routing problems while maintaining small errors.

Keywords: Artificial Intelligence, Manufacturing upgrade, Gray Relational Analysis Method

1 Introduction

In December 2025, the Ministry of Industry and Information Technology, together with the Cyberspace Administration of China, the National Development and Reform Commission, and several other departments, issued the "Implementation Opinions on the Special Action for 'AI + Manufacturing'." This further clarified that AI technology is a core element in advancing new types of productivity and new industrialization. It also provided clear guidance for AI to empower key sectors in the manufacturing industry to transform. To promote further development of AI-empowered manufacturing, Chongqing introduced related policies, including the '33618' modern manufacturing cluster system. As an important sub-center city of Chongqing, Wanzhou District has already begun to build the '3233' modern manufacturing system.

From the literature review, scholars at home and abroad generally recognize that AI positively promotes manufacturing and enables industrial upgrading. Currently, many studies focus on the transformation of relatively mature industrial clusters^[1-3], for example, Zhang Chunmei used data from 3,288 Chinese A-share manufacturing companies between 2010 and 2025 to empirically test the impact of AI on total factor produc-

tivity in manufacturing and its mechanisms. Some studies focus on analyzing the internal mechanisms and paths through which AI technology empowers industrial upgrading^[4-5], for example, Du Chuanzhong analyzed the mechanisms and paths of deep integration in manufacturing based on AI's data-driven and tech-economic paradigm characteristics. But there are still gaps in current research: there are few empirical studies targeting underdeveloped industrial counties in northeastern Chongqing combined with local specialized industry policies, and systematic research specifically focusing on the integration of AI and manufacturing in Wanzhou District is scarce, making it difficult to meet the personalized transformation and development needs of the region.

2 Basic Concepts and an Overview of the Manufacturing Industry in Wanzhou District

2.1 Definition of concepts

(1) Concept of Manufacturing Industry

According to the 'National Economic Industry Classification (2017)' and the International Federation of Robotics' 'International Standard Industrial Classification (ISIC Rev4.0),' and with reference to the research by Wang Fang and Shi Xin, 28 industries are categorized by the intensity of industry technology demand into three major types: low-tech manufacturing, medium-tech services, and high-tech manufacturing, represented by I, II, and III, respectively. Since manufacturing sub-industries are relatively complex, each industry has a corresponding industry code, which helps facilitate more in-depth analysis. Industry classification information is shown in Table 1.

Table 1. Classification and Categories of the Manufacturing Industry

Industry code	Industry Name	Industry type	Industry code	Industry Name	Industry type
C13	Agricultural and sideline food processing industry	I	C25	Petroleum, coal, and other fuel processing industries	II
C14	Food Manufacturing Industry	I	C26	Manufacture of chemical raw materials and chemical products	III
C15	Alcohol, Beverage, and Refined Tea Manufacturing Industry	I	C27	Pharmaceutical Manufacturing Industry	III

Industry code	Industry Name	Industry type	Industry code	Industry Name	Industry type
C16	Tobacco products industry	I	C28	Chemical fiber manufacturing industry	III
C17	Textile industry	I	C29	Rubber and Plastics Products Industry	II
C18	Textile and apparel, clothing and accessories industry	I	C30	Non-metallic Mineral Products Industry	II
...					

(2) Artificial Intelligence

In December 2018, the National Bureau of Statistics released the "Classification of Strategic Emerging Industries (2018)", listing the artificial intelligence industry as a subfield of the new generation information technology industry. This industry is divided into three main parts: artificial intelligence software development, manufacturing of intelligent consumer-related devices, and artificial intelligence system services. The specific classification can be seen in Table 2. Its system indicators are shown in Table 3. Its system indicators refer to reference 4.

Table 2. Classification of the Artificial Intelligence Industry

Category Name	Explanation
Artificial Intelligence Software Development	Including software development related to artificial intelligence, such as machine learning algorithms, natural language processing tools, etc.
Manufacturing of smart consumer-related devices	Involves the manufacturing of smart consumer hardware such as smart home and wearable devices
Artificial Intelligence System Services	Provide integration, operation and maintenance, and related services for artificial intelligence systems

2.2 Overview of Manufacturing in Wanzhou District

(1) Overview of Wanzhou Industry

According to the 25-year Wanzhou District Statistical Yearbook data, from 2015 to 2025, the output value of the secondary industry in Wanzhou District increased from 26.87 billion yuan to 42.5 billion yuan, with a compound growth rate of 4.77%. Among

them, the industrial sector, as the core of manufacturing, performed even more prominently, with output value rising from 15.836 billion yuan to 25.734 billion yuan, a compound growth rate of 5.54%, which is significantly higher than construction (3.64%) and the overall level of the secondary industry. From the internal structure of the secondary industry, the proportion of industrial (manufacturing) output value in the secondary industry increased from 58.94% in 2015 to 62.98% in 2025, an increase of 4.04 percentage points over the past decade, continuously strengthening the core supporting role of manufacturing in the secondary industry. The data are shown in Figure 1 below.

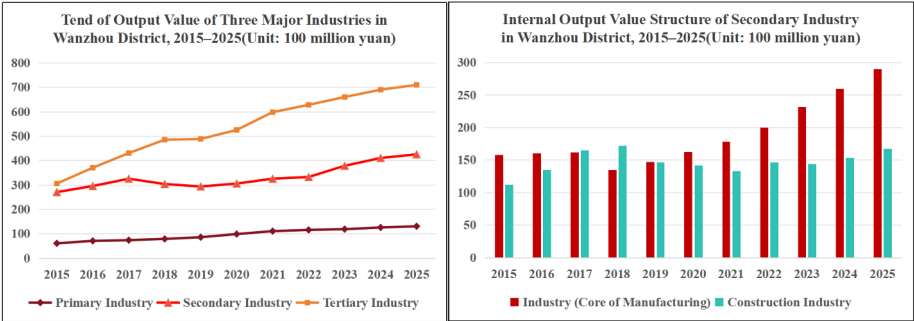


Fig. 1. Overview of Industrial Data in Wanzhou District

From the perspective of investment in construction projects in the secondary industry manufacturing sector, fixed asset investment in manufacturing accounts for 84.5% of the secondary industry and 33.7% of the overall industry structure. Fixed asset investment increased from 6,120.7 million yuan in 2023 to 7,291.89 million yuan in 2025. In 2025, the manufacturing industry has 89 investment projects, including construction and production projects, with a project completion and production rate of 49.4%.

From the overall data, the secondary industry in Wanzhou District steadily expanded from 2015 to 2025, showing strong resilience in industrial growth. The internal structure continued to optimize, with the manufacturing industry leading the growth of the secondary industry and its share increasing year by year, further highlighting its dominant supporting role. At the same time, the fixed asset investment in manufacturing increased in scale, and its industry proportion became prominent, showing a clear investment-driven effect. The implementation and production of industrial projects were advancing effectively, presenting an overall good development trend characterized by scale expansion, structural upgrading, increased investment, and industry-led growth.

(2) Number and Scale of Industrial Enterprises in Wanzhou

According to the 25-year industry breakdown, there are 1,831 corporate entities, 1,863 industrial activity units, and 4,074 individual industrial and commercial households in the manufacturing sector.

There are 214 large-scale enterprises in the whole district (with annual main business revenue over 5 million), and the total industrial output in 2025 reached 71.917 billion yuan. Among them, 35 companies are operating at a loss, making the overall loss rate about 17.3%. The industry's operation is generally stable, but there is a gap in profitability. Industries like equipment manufacturing, material processing, and energy supply

dominate the market. There are 53 equipment manufacturing companies in total, including automobile manufacturing and electrical machinery, showing a clear industrial cluster effect.

The output value of the non-ferrous metal smelting and rolling processing industry exceeded 30.174 billion yuan, accounting for 42% of the total output value of the entire district, making it the core pillar of Wanzhou's industry. The output value of the four major industries—automobile manufacturing, electric power and heat, electrical machinery, and chemical raw materials—each exceeded 6 billion yuan, together accounting for 34.7% of the district's total output value, and along with the first-tier industries, support nearly 87% of the district's industrial output value.

With the rise of artificial intelligence, Wanzhou District has also been paying attention to the development of the manufacturing industry, successively issuing several policy measures. In 2025, 16 new above-scale industrial enterprises were added, 17 specialized, refined, distinctive, and innovative small and medium-sized enterprises were cultivated, 4 gazelle companies emerged, and 1 national-level intelligent manufacturing demonstration factory, as well as 6 municipal-level smart factories and digital workshops were newly established. Among them, Jinlong Copper Pipe became the first 20-billion-level industrial enterprise in the district, and Jiulong Wanbo's output value exceeded 18 billion yuan. This survey mainly targets the whitelist of manufacturing enterprises in Wanzhou District.

3 Analysis of the Current Situation of Artificial Intelligence and Manufacturing Upgrading in Wanzhou District

3.1 Analysis of the Current Level of Artificial Intelligence in Wanzhou District

(1) Measurement model construction

This paper uses the entropy method to calculate the comprehensive score of each indicator (based on the indicator system in reference 4) as a measure of the level of artificial intelligence development. The specific calculation formulas and steps are as follows^[4]:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (1)$$

② Use the entropy method to determine the indicator weights

Calculate the proportion of the i -th scheme's indicator value under the j -th indicator:

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (2)$$

Calculate the entropy value of the j -th evaluation indicator:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln(p_{ij}), k > 0, 0 \leq e_j \leq 1 \quad (3)$$

Calculate the coefficient of variation for each indicator:

$$d_j = 1 - e_j \quad (4)$$

③ Calculate the weight of the j -th evaluation index:

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j}, j = 1, 2, \dots, n \quad (5)$$

④ Calculate the comprehensive score of artificial intelligence development level:

$$Z_j = \sum_{j=1}^m w_j y_{ij}, j = 1, 2, \dots, m \quad (6)$$

(2) Analysis of Measurement Results

During the period from 2015 to 2025, the level of artificial intelligence development in Wanzhou District has improved overall. Overall, the development of artificial intelligence in Wanzhou District has undergone an evolution from initial exploration (2015-2018) to rapid growth (2018-2021), and then to gradual maturity (2021-2025). The time trend chart of the overall artificial intelligence development index for Wanzhou District and Chongqing Municipality is shown in Figure 2.

In the early stage (2015-2018), the overall level of artificial intelligence development in Chongqing was relatively low. In 2015, the city's average development level was only 0.17, and Wanzhou District was just close to the city average. During this stage, AI technology was still in the initial development phase, application scenarios were limited, and there was a shortage of related infrastructure and talent reserves.

Entering the rapid development stage (2018-2021), artificial intelligence experienced explosive growth across the city. By 2021, the city's average development level had risen to 0.44, with a slight decline between 2020 and 2021; however, Wanzhou District's AI development level increased year by year, approaching the city-wide level, reaching 0.43. During this period, with the popularization of technologies such as big data and cloud computing, and the elevation of AI's strategic status by the national government, various districts increased their investments in artificial intelligence.

In the stable growth stage (2021-2025), AI development gradually entered a mature period. By 2025, the city's average development level had increased to 0.55, with Wanzhou District reaching the average level and expected to surpass the city average. During this period, the commercialization of technology continued to deepen, and market competition became increasingly intense.

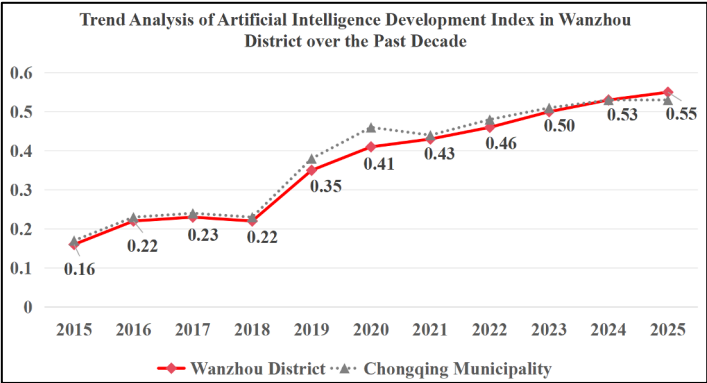


Fig. 2. Trend Analysis of Artificial Intelligence Development Index in Wanzhou District over the Past Decade

3.2 Analysis of the Current Status of Manufacturing Industry Upgrading in Wanzhou District

(1) Measurement Model Analysis

This paper constructs an indicator system for manufacturing upgrading based on the research methods of Reference 4, analyzing the upgrading level of the manufacturing industry in Wanzhou District from three dimensions: high-end, intelligent, and green development of manufacturing. The specific data sources are the Wanzhou District Statistical Yearbook, corporate annual reports, association statistical yearbooks, etc., and missing data are filled using methods such as linear interpolation. This paper selects 31 major manufacturing industry categories, including food, chemical, textile, pharmaceutical, machinery, and electronics, with specific classifications shown in Table 1 above.

(2) Analysis of Measurement Results

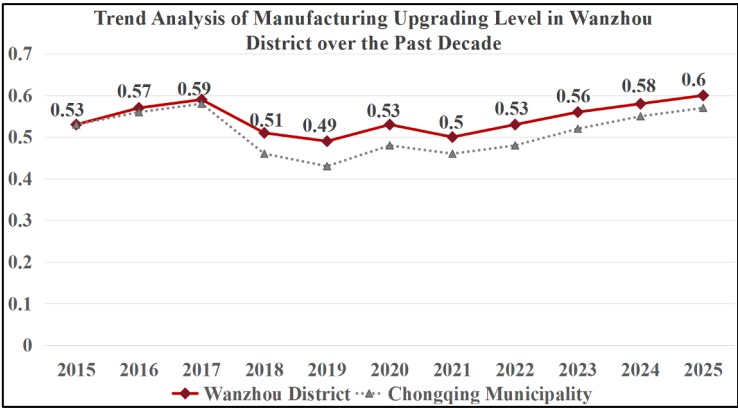


Fig. 3. Trend Analysis of Manufacturing Upgrading Level in Wanzhou District over the Past Decade

This article measures the manufacturing upgrading level of the entire Chongqing Municipality and Wanzhou District from 2015 to 2025 based on the manufacturing upgrading indicator system. The results are shown in Figure 3. From 2015 to 2025, the average value of manufacturing upgrading in the whole city shows an overall upward trend, but it declined in 2019 due to the impact of the pandemic, falling to 0.49. Although it slightly increased after the pandemic, the effect was not significant, and it was not until after 2022 that it rose to 0.53. From 2021, the growth rate of the manufacturing upgrading index accelerated, especially in 2023 and 2025, where the increase was more significant. By 2025, the manufacturing upgrading level reached 0.60, indicating a relatively stable development level with a yearly increasing trend.

4 An Empirical Analysis of the Impact of Artificial Intelligence on the Upgrading of Manufacturing in Wanzhou District

The intelligent transformation of manufacturing in Wanzhou District started relatively late, with limited data samples and unclear influencing factors, making it a typical gray system. At the same time, it is necessary to quantify the causal effect of artificial intelligence on manufacturing upgrading. Therefore, this paper designs a two-stage modeling approach:

First stage: Grey Relational Analysis (GRA): Suitable for small sample and non-normally distributed data characteristics, it quantifies the strength of the association between various artificial intelligence influencing factors and manufacturing upgrading, and screens the core key variables.

Second stage: Benchmark regression model: Referring to the provincial-level panel research paradigm, benchmark regression, mediation effect, and moderation effect models are constructed to test the impact mechanism of key factors on manufacturing upgrading, complementing the limitation of grey relational analysis that can only reflect correlations.

4.1 Model construction

(1) Variable Design

Table 3. Scalar Design Parameters

Variable type	Variable	Interpretation
Dependent Variable (Level of Manufacturing Upgrading)	(MUI)	Select the industrial added value of above-scale manufacturing in Wanzhou District as the core indicator, and construct a comprehensive index from the dimensions of high-end, intelligent, and green development, keeping consistent with the dependent variable setting of the benchmark regression model.
Core explanatory	AI ₁	AI and Industrial Internet Technology Reform Investment Amount (100 million yuan)

variables (key factors of artificial intelligence (AI))	AI_2	Number of enterprise AI application scenarios
	AI_3	Manufacturing R&D Expenditure (100 Million Yuan)
	RDI	The R&D innovation capability uses the entropy method to synthesize a comprehensive score
Mediator variable	GTEP	Green total factor productivity of manufacturing, measured using the super-efficiency SBM model
Control variable (government subsidies for manufacturing)	SUB	Special Financial Subsidy Amount for Intelligent Manufacturing (ten thousand yuan)
	open	Degree of openness to the outside world, proportion of total import and export of manufacturing in GDP
	Gap	Income gap between urban and rural residents, the ratio of per capita disposable income of urban and rural residents
	Ind	Level of industrialization, proportion of industrial added value in GDP
	Gov	Government regulation intensity, proportion of fiscal expenditure to GDP
Control variable	Info	Level of information technology, number of internet broadband access users

(2) Grey Relational Analysis and Key Factor Screening

Set the manufacturing upgrade level as the system reference parent sequence, and the various influencing factors of artificial intelligence as the comparative sub-sequences. The classical Deng's grey relational model is used for calculation, with the specific steps as follows:

① Dimensionless processing

To eliminate differences in dimensions among different indicators, the initial value method is used to standardize all data. The formula is:

$$x'_i(k) = \frac{x_i(k)}{x_i(1)}, x'_0(k) = \frac{x_0(k)}{x_0(1)} \quad (7)$$

Where: $x_0(k)$ is the original data of the mother sequence (manufacturing upgrade level) for year i , $x_i(k)$ is the original data of the j -th subsequence (artificial intelligence influencing factor) for year i , $x_0(1)$, $x_i(1)$ is the value of the corresponding index in the base period (2018), and $x'_0(k)$, $x'_i(k)$ is the standardized sequence value.

② Calculate the absolute difference sequence

Solve for the annual absolute difference between the standardized parent sequence and each subsequence, reflecting the degree of deviation in their change trends:

$$\Delta_i(k) = |x'_0(k) - x'_i(k)| \quad (8)$$

③ Solve for the global extreme values

Calculate the global minimum difference and global maximum difference among the differences of all years and all subsequences, providing a reference scale for the calculation of the correlation coefficient:

$$\Delta_{\min} = \min_i \min_k \Delta_i(k), \Delta_{\max} = \max_i \max_k \Delta_i(k) \quad (9)$$

④ Correlation Coefficient and Degree of Correlation Calculation

Set the resolution coefficient $\rho = 0.5$ (commonly used standard in academia), calculate the single-year correlation coefficient, and then obtain the comprehensive degree of correlation through the arithmetic mean:

$$\xi_i(k) = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_i(k) + \rho \Delta_{\max}}, \gamma_i = \frac{1}{7} \sum_{k=1}^7 \xi_i(k) \quad (10)$$

Here, $\xi_i(k)$ is the correlation coefficient of the n th factor in the m th year, and γ_i is the comprehensive correlation degree between the n th factor and manufacturing upgrading.

(3) Construction of the Benchmark Regression Model

Construct a benchmark regression model of key artificial intelligence factors on manufacturing upgrading, and test the net effect of the core variables:

$$MUI_t = \alpha_0 + \alpha_1 AI_t + \sum_{j=1}^5 \alpha_j Controls_t + \lambda_t + \varepsilon_t \quad (11)$$

Where: represents the year, Controls is the control variable, λ_t is the time fixed effect, ε_t is the random error term, and α_1 reflects the impact of key artificial intelligence factors on the upgrading of the manufacturing industry.

To examine the path through which artificial intelligence empowers the upgrading of the manufacturing industry, this paper constructs a mediation effect model with reference to Jiang Ting's analytical method, using R&D innovation capability (RDI) and green total factor productivity of the manufacturing industry (GTEP) as mediating variables. The specific model is as follows:

$$RDI_t = \beta_0 + \beta_1 AI_t + \sum_{j=1}^5 \beta_j Controls_t + \lambda_t + \varepsilon_t \quad (12)$$

$$GTEP_t = \gamma_0 + \gamma_1 AI_t + \sum_{j=1}^5 \gamma_j Controls_t + \lambda_t + \varepsilon_t \quad (13)$$

To explore the moderating effect of government subsidies for the manufacturing industry on the relationship between artificial intelligence and manufacturing upgrading, this paper introduces a moderating effect model based on the benchmark regression model, with the formula as follows:

$$MUT_t = \delta_0 + \delta_1 AI_t + \delta_2 SUB_t + \delta_3 AI_t \times SUB_t + \sum_{j=1} \delta_j Controls_t + \lambda_t + \varepsilon_t \quad (14)$$

Where: *SUB* represents government subsidies for the manufacturing industry, and *AI* × *SUB* serves as the interaction term between artificial intelligence and manufacturing industry government subsidies.

4.2 Model empirical analysis

(1) Grey relational analysis

Table 4 presents the descriptive statistics of each variable, intuitively showing the mean, standard deviation, extreme values, and other statistical characteristics of the variables during the sample period, providing basic data support for subsequent empirical analysis.

There are a total of 7 observation years, and all variables have been standardized. The standard deviation of the dependent variable is relatively small, indicating that the level of manufacturing upgrading in Wanzhou District has been steadily increasing year by year, with low volatility. Among the core explanatory variables, the standard deviation of *AI*₁ reaches 1.023, with a maximum value of 3.936, much higher than other variables, indicating that investment in AI technological transformation has the largest growth range during the sample period and exhibits significant phased investment characteristics, making it a key focus of regional industrial investment; *AI*₂、*AI*₃ grows relatively steadily, reflecting that the implementation of AI scenarios and R&D funding maintain stable growth.

Table 4. Analysis of Descriptive Statistics of Variables

Variable symbol	Standard deviation	Minimum value	Maximum value	Variable symbol	Standard deviation	Minimum value	Maximum value
(MUI)	0.256	1.000	1.861	SUB	0.587	1.000	2.876
<i>AI</i> ₁	1.023	1.000	3.936	open	0.045	0.123	0.265
<i>AI</i> ₂	0.785	1.000	3.214	Gap	0.152	2.012	2.587
<i>AI</i> ₃	0.692	1.000	2.987	Ind	0.034	0.301	0.412
RDI	0.164	0.321	0.892	Gov	0.056	0.213	0.378
GTEP	0.123	0.912	1.345	Info	0.121	0.487	0.876

(2) Baseline regression model test

The benchmark regression results are shown in Table 5.

Table 5. Analysis of Benchmark Regression Results

Variable	Model (1) (MUI)	Model (2) (MUI)	Model (3) (MUI)	Model (4) MUI (Full control)
AI ₁	0.312*** (0.045)	-	-	0.208** (0.061)
AI ₂	-	0.287*** (0.052)	-	0.175** (0.058)
AI ₃	-	-	0.254** (0.063)	0.142* (0.065)
open	-	-	-	0.121 (0.087)
Gap	-	-	-	-0.098* (0.041)
Ind	-	-	-	0.187** (0.059)
Gov	-	-	-	0.087 (0.072)
Info	-	-	-	0.154* (0.068)
constant term	0.654***	0.712***	0.785***	0.421**
Time Fixed Effects	Control	Control	Control	Control
R ²	0.923	0.901	0.876	0.965
N	7	7	7	7

From the perspective of goodness of fit, the full-variable Model $R^2 = 0.965$ has an excellent overall fit and strong explanatory power. In both the stepwise regression and the full control variable model, the coefficients of the three core explanatory variables are all significantly positive, proving that investments and applications related to artificial intelligence can significantly promote the upgrading of the manufacturing industry in Wanzhou District. By comparing the sizes of the coefficients, it can be seen that coefficient AI₁ is the largest, followed by AI₂、AI₃, indicating that the driving effect of investment in intelligent technological transformation is the strongest, the implementation of AI scenarios comes next, and the driving effect of R&D investment is relatively weak.

(3) Mediation Effect Model Testing

The results of the mediating effect test are shown in Table 6. Taking the core variable as an example, Model (1) is the baseline regression, Models (2) and (4) are the regressions with the mediating variables, and Models (3) and (5) are the regression results

after including the mediating variables, verifying the mediating paths of R&D innovation and green total factor productivity.

Table 6. Mediation Effect Test Results

Variable	Model (1) (MUI)	Model (21) (MUI)	Model (3) (MUI)	Model (4) GTEP	Model (5) (MUI)
AI ₁	0.208** (0.061)	0.187** (0.054)	0.142* (0.065)	0.154** (0.048)	0.131* (0.062)
RDI	-	-	0.354** (0.102)	-	-
GTEP	-	-	-	-	0.412** (0.115)
Control variable	Control	Control	Control	Control	Control
Time Fixed Effects	Control	Control	Control	Control	Control
R ²	0.965	0.932	0.978	0.915	0.972
N	7	7	7	7	7

Taking A as an example, the coefficient of B on the intermediary variable C is significantly positive, indicating that investment in artificial intelligence technological transformation can effectively enhance enterprises' R&D innovation capability and green total factor productivity. Second, after including the intermediary variable, the coefficient of D decreases but remains significant, while the coefficient of E is significantly positive, proving that R&D innovation and green total factor productivity have a partial mediating effect between artificial intelligence and manufacturing upgrading.

(4) Moderation Effect Model Test

The results of the moderation effect test are shown in Table 7.

Table 7. Test Results of the Moderating Effect

Variable	Model (1) (MUI)	Model (2) (MUI)	Model (3) (MUI)
AI ₁	0.208** (0.061)	0.192** (0.063)	0.165* (0.068)
SUB	-	0.121* (0.052)	0.108* (0.055)
AI ₁ × SUB	-	-	0.087** (0.031)
Control variable	Control	Control	Control

Time Fixed Effects	Control	Control	Control
R ²	0.965	0.971	0.982
N	7	7	7

After gradually adding government subsidies and interaction terms, the model's goodness of fit continued to improve. The coefficient of SUB is significantly positive, indicating that financial subsidies for smart manufacturing themselves can promote the upgrading of the manufacturing industry; the coefficient of the core interaction term $AI_1 \times SUB$ is significantly positive at the 5% level, showing that government subsidies have a significant positive moderating effect. That is, financial support policies can amplify the driving effect of artificial intelligence investment on manufacturing upgrading, and policy tools and smart investment form a virtuous synergy. This also implies that the current smart manufacturing subsidy policy in Wanzhou District is effective, and continuously increasing policy support can further unleash the industrial empowerment potential of artificial intelligence.

5 Conclusion

Combining the previous gray relational analysis with the empirical results of benchmark regression, it is evident that investment in AI technology transformation, scenario-based application, and R&D expenditure are the three core drivers of manufacturing upgrading in Wanzhou District. Meanwhile, information infrastructure and government subsidy policies have a positive supporting effect, whereas the urban-rural income gap imposes certain constraints. Based on the empirical findings and taking into account the current state of regional industrial development, three layered and actionable development paths are identified.

First, strengthen investment in intelligent technology transformation to consolidate the industrial hardware foundation. Empirical evidence shows that AI technology transformation investment has the strongest driving effect on manufacturing upgrading. The local area should continue to increase funding in industrial internet and intelligent production equipment, guiding traditional manufacturing enterprises to carry out intelligent upgrades of production lines, prioritizing leading industry clusters. Hardware upgrades can directly improve production efficiency and industrial capability, playing a core role in driving capital investment.

Second, expand AI application scenarios to promote technology integration on the ground. The empowerment effect of AI scenario applications ranks second only to technology transformation investment. On one hand, based on local manufacturing operations, promote AI technologies in production management, quality inspection, warehousing, logistics, and other aspects. On the other hand, build government-enterprise collaborative platforms to advance the deep integration of technology and the real economy, avoiding idle technological deployment, and ensuring that artificial intelligence continuously delivers value in actual production.

Third, increase the allocation of R&D resources to improve long-term innovation mechanisms. The driving effect of R&D investment is relatively weak and should be a

focus for future optimization. The region needs to steadily increase the scale of manufacturing R&D funding, encourage enterprises to collaborate with local research institutions on intelligent technology breakthroughs, and cultivate independent innovation capabilities. At the same time, effectively utilize fiscal subsidy policies to exert positive regulatory effects, reducing enterprise R&D and transformation costs through policy support.

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References

1. Zhang Chunmei, Xu Tengfei, Xia Danying, et al. How Artificial Intelligence Empowers High-Quality Development of the Manufacturing Industry—From the Perspective of Total Factor Productivity [J]. *Enterprise Economy*, 2026, 45(6):94-104. DOI: 10.13529/j.cnki.enterprise.economy.2026.06.009.
2. Geng Ziheng, Li Jianning, Sun Feihong. Generative Artificial Intelligence Empowering Green Development in Manufacturing: Theoretical Mechanisms, Practical Challenges, and Implementation Pathways [J]. *Price Theory and Practice*, 2026, (1):159-165 291. DOI:10.19851/j.cnki.CN11-1010/F.2026.01.021.
3. Liu Xiaonan, Chen Yunping. Artificial Intelligence and Virtual Clustering in the Manufacturing Industry [J/OL]. *Contemporary Finance & Economics*, 2026, (6): 73-85 [2026-06-25]. <https://doi.org/10.13676/j.cnki.cn36-1030/f.20260116.002>.
4. Ma Yufei. Research on the Promotion of Manufacturing Upgrading by Artificial Intelligence [D]. Harbin University of Commerce, 2025. DOI: 10.27787/d.cnki.ghrbs.2025.000652.
5. Liu Jiahui. Artificial Intelligence and the Resilience of the Manufacturing Industry Chain: Mechanisms and Empirical Tests [D]. Zhejiang University of Finance and Economics, 2025. DOI: 10.27766/d.cnki.gzjcj.2025.000007.

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