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Article

Research on the Mechanism of Artificial Intelligence-Driven Government Innovation Services to Enhance Manufacturing Innovation Capabilities

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Abstract: The rapid development of artificial intelligence has injected new momentum into manufacturing enterprises to enhance their independent innovation capabilities and strengthen their competitive advantages. Manufacturing enterprises should actively adapt to this development trend, seize the driving force provided by technological development, and enable Chinese manufacturing to form new advantages in global market competition. Therefore, this paper comprehensively reviews scholars' research on the artificial intelligence transformation of manufacturing and manufacturing innovation capabilities, proposes the theoretical foundation of innovation-driven and endogenous growth, and analyzes the current level of innovation capabilities of manufacturing enterprises under artificial intelligence technology. Using a two-way fixed effects model, we constructed a measurement framework and proposed relevant research hypotheses, designing a basic regression and mechanism testing model to analyze each research hypothesis individually. The findings indicate that the regression coefficient for the impact on the number of R&D personnel is 1.648, which is significantly positive at the 1% level. The application of artificial intelligence can increase the number of R&D personnel in an enterprise and promote employee participation in process innovation, thereby validating Hypothesis 1. Mediation effect tests were conducted simultaneously for industry type, innovation strategy, and government subsidies. When the explained variable was corporate innovation performance, the regression coefficients for industry type, innovation strategy, and government subsidies were 0.186, 0.197, and 0.185, respectively, all of which were significantly positive at the 5% level. This indicates that improvements in industry type, innovation strategy, and government subsidies can positively influence corporate innovation performance, thereby validating Hypotheses 2, 3, and 4.

Keywords: Two-way fixed effects; mechanism testing model; endogenous growth; artificial intelligence technology; manufacturing innovation capability

1. Introduction

In recent years, with the rapid development of science and technology, the manufacturing industry is undergoing a profound transformation [1]. Innovation capacity, as one of the key factors driving the development of the manufacturing industry, is increasingly being recognized [2]. The enhancement of innovation capacity in the manufacturing industry not only has a significant impact on the development of enterprises themselves but also exerts a far-reaching influence on the entire industrial chain and national economic development [3-5]. To achieve the enhancement of innovation capacity in the manufacturing industry, support from government innovation services is indispensable [6].

To enhance manufacturing innovation capabilities, it is essential to fundamentally alter the past reliance on external technology imports [7]. First, the government should significantly increase fiscal investments, encourage enterprises to allocate more funds to independent research and development, and establish a comprehensive financial support mechanism [8-9]. Concurrently, efforts should be made to optimize the allocation of research resources and project management, identify issues during research, and expedite their conversion into practical applications [10-11]. Second, enhancing manufacturing innovation capabilities necessitates a strong emphasis on the protection and utilization of intellectual property rights [12]. The government needs to improve laws and regulations, establish a sound intellectual property system, and crack down on infringement [13]. At the same time, it should strengthen training and publicity on intellectual property rights for enterprises to enhance their awareness and capabilities in protecting intellectual property rights [14]. Additionally, the government should increase support for manufacturing innovation, formulate relevant policies, and establish a sound innovation support system centered on industry-academia-research collaboration [15-16]. Reducing investment and operational risks in technology transfer can encourage enterprises to innovate more boldly during the R&D process [17]. Only through these efforts can China's manufacturing industry be driven toward higher levels of development and achieve sustainable growth driven by innovation [18-19].

Literature [20] aims to provide evidence on the impact of innovation on product quality, operational performance, and financial performance of enterprises. Based on a study of sample enterprises, it was found that “innovation capability” has a direct impact on product quality and operational performance. Literature [21] points out that the number of small and medium-sized manufacturing enterprises that have successfully embraced the digital transformation envisioned by Industry 4.0 is currently limited, emphasizing that the reason lies in the need for significant innovation in manufacturing systems to achieve this transformation. Through case analysis, it reveals the various capabilities required for successful manufacturing innovation. Literature [22] aims to determine the impact of innovation capabilities in manufacturing enterprises on multi-channel integration and its effects on corporate performance, revealing that the stronger an enterprise's innovation capabilities, the higher its level of multi-channel integration. Literature [23] builds a structured model based on the knowledge base and knowledge creation theory, discussing the relationship between innovation capabilities, disruptive technologies, and knowledge creation, as well as their impact on corporate development. The results show that innovation capabilities, disruptive technologies, and knowledge creation have a positive impact on sustainable development. Literature [24] highlights China's outstanding achievements in manufacturing, emphasizes the importance of innovation for industrial upgrading, and analyzes the impact of innovation capability, production capability, and vertical specialization on innovation performance from both supply and demand perspectives. The results indicate that innovation inputs and outputs exhibit significant regional heterogeneity in China. Literature [25] examines the potential structure of employee autonomy and innovation capabilities and their interactions, using the German manufacturing sector as an example to separate innovation capability clusters, which classify manufacturing employees into potential, passive balance, and autonomous leaders. Literature [26] aims to verify the path relationship between the strength of ties, absorption capacity, and innovation performance of Chinese manufacturing enterprises, indicating that enterprise absorption capacity plays a significant mediating role in the relationship between tie strength and innovation performance. Literature [27] emphasizes the importance of innovation capabilities for enterprise development and investigates the factors influencing manufacturing enterprises' innovation capabilities. The results indicate that inter-organizational cooperation and internal R&D expenditures are key drivers of manufacturing enterprises' innovation capabilities.

This paper begins by defining the concept of intelligent manufacturing in manufacturing enterprises, analyzes the process of intelligent manufacturing in such enterprises, and explores the mechanisms through which it enhances manufacturing innovation capabilities. It conducts an in-depth study of R&D mechanisms, introduces an endogenous growth model, and proposes a vertical innovation model based on this framework. The paper analyzes the current status of artificial intelligence technology and innovation in manufacturing enterprises from two perspectives: inputs and outputs. Using a two-way fixed effects econometric model, the study identifies the impact of artificial intelligence on manufacturing innovation and its underlying mechanisms, and proposes relevant research hypotheses. Corresponding variables are selected, and basic regression and mechanism testing models are designed. Techniques such as difference-in-differences and mediation effect tests are employed to verify the validity of the hypotheses proposed earlier. Based on the research findings, the study summarizes its limitations, suggests potential directions for improvement, and lays the groundwork for more in-depth research in the future.

2. Concepts and theoretical foundations of artificial intelligence and manufacturing innovation capabilities

2.1. Definition of Related Concepts

2.1.1. Artificial Intelligence in Manufacturing

The intelligentization of manufacturing is a crucial process in driving the realization of smart manufacturing. Academic discussions on the essence of manufacturing intelligentization primarily stem from the conceptual definition of smart manufacturing itself.

This paper argues that manufacturing intelligentization is a process that leverages artificial intelligence technology and industrial informatization to achieve technological breakthroughs, ultimately realizing smart manufacturing [28]. The fundamental purpose of manufacturing intelligence is to achieve a transformation in production or operational methods through the iterative upgrading of artificial intelligence and information technology, thereby facilitating a shift from low-value-added to high-value-added production. In the process of manufacturing intelligence, it can be deconstructed as an investment in intelligent equipment and technologies based on the integration of informatization and industrialization, enabling intelligent applications in production processes to achieve both social and economic benefits.

2.1.2. Manufacturing Innovation Capabilities

Innovation capacity is a key indicator of a country's core competitiveness, and technological innovation serves as the driving force behind innovation-driven development. The concept of innovation capacity was first proposed by a certain scholar, who viewed innovation as an economic concept rather than a technical one, defining it as a new ratio of input among production factors aimed at enhancing society's potential productive capacity.

This paper synthesizes the research of the aforementioned scholars and defines innovation capacity as the ability of a region to drive economic growth through innovation entities such as governments, universities, enterprises, research institutions, and financial institutions, leveraging internal innovation resources to continuously produce new products with economic and social value in fields such as technology and production activities. The formation of innovation capacity is a process of continuously developing innovation inputs, innovation outputs, and innovation technology acquisition capabilities within a specific innovation environment.

2.2. Theoretical Basis

2.2.1. Innovation-driven theory

A scholar first proposed the impact of technological innovation on economic growth, pointing out that the promotional effect of technological progress on economic growth is achieved through labor division, and this process is driven by innovation [29]. The term “innovation-driven” was first coined by an American management scholar, who analyzed the process of economic development and categorized it into four stages: “factor-driven,” “investment-driven,” “innovation-driven,” and “wealth-driven.” This theory posits that the three drivers—factor-driven, investment-driven, and innovation-driven—are the primary sources of a nation's competitive advantage, typically accompanying economic prosperity. Therefore, implementing innovation-driven development can promote sustainable economic growth, facilitate national economic development, and enhance international competitiveness. In the face of the unprecedented changes in the world today, innovation-driven development has emerged as a fundamental driving force for China's high-quality development. The integration of innovation with industrial development can better advance industrial transformation and upgrading, playing a crucial role in the faster and higher-quality construction of China's modern industrial system.

2.2.2. Endogenous Growth Theory

In the mid-1980s, scholars proposed the endogenous growth theory, which is an important branch of macroeconomic theory. The core idea of this theory is that the decisive factor promoting sustainable economic growth is technological progress. Regarding economic growth, scholars as early as the classical economics period proposed that technological progress promotes economic growth through the division of labor. Later, they emphasized that reasonable income distribution has a positive effect on economic growth. The neoclassical economic growth theory model divides the factors influencing economic growth into two parts: input of production factors and technological progress. The impact of production factors on economic growth only has a horizontal effect and no growth effect, while the fundamental factor determining economic growth is actually technological progress. These theories laid the ideological foundation for the subsequent development of endogenous growth theory, which first introduced technological progress into the endogenous growth model, conducted in-depth research on R&D models, and based on this, proposed vertical innovation models. Such models incorporate technological progress into the endogenous growth model:

$$Y = H^{\alpha} L^{\beta} \int_{n}^{A} X_{i}^{1-\alpha-\beta} d_{i}, 0 < \alpha, \beta < 1 \tag{1}$$

In Equation (1), Y represents output, H represents human capital, L represents the quantity of general labor, X represents the quantity of intermediate products, and A represents the types of intermediate products. As can be seen from the production function, the types and quantities of intermediate products have a certain impact on output. As long as enterprises continue to research and develop new intermediate products, they will drive long-term economic growth. Therefore, for the manufacturing industry, to improve output levels and stimulate endogenous growth momentum, it is necessary to continuously engage in innovation and research and development, promote technological innovation, and facilitate transformation and upgrading.

3. Analysis of the Current State of Artificial Intelligence and Innovation in Manufacturing Enterprises

3.1. Artificial Intelligence

The accelerating evolution of artificial intelligence has brought about significant changes in international market competition. To adapt to new domestic and international development needs, China has achieved a series of accomplishments in artificial intelligence technological innovation, which are mainly reflected in terms of investment and output.

3.1.1. Current Status of R&D Expenditure Funding

The following analysis will examine the current state of investment in artificial intelligence (AI) technology innovation in China from two perspectives: total R&D expenditure across society and the status of R&D personnel [30].

Figure 1 shows China's R&D expenditure from 2013 to 2023. In 2023, the total R&D expenditure reached 3.816 trillion yuan, an increase of 2.787 trillion yuan over the past decade, with an average annual growth rate of 15.973%, ranking second in the world. In terms of R&D funding for basic research, 2024.648 billion yuan was invested in 2023, nearly four times the amount in 2013. However, it is also important to note that in 2023, basic research accounted for only 6.636% of China's total R&D spending, while developed countries maintain a stable ratio of over 12%. This disparity highlights China's insufficient capacity for original innovation and relatively low efficiency in scientific and technological innovation, indicating that China's investment in basic research remains relatively inadequate, which may lead to low rates of innovation conversion.

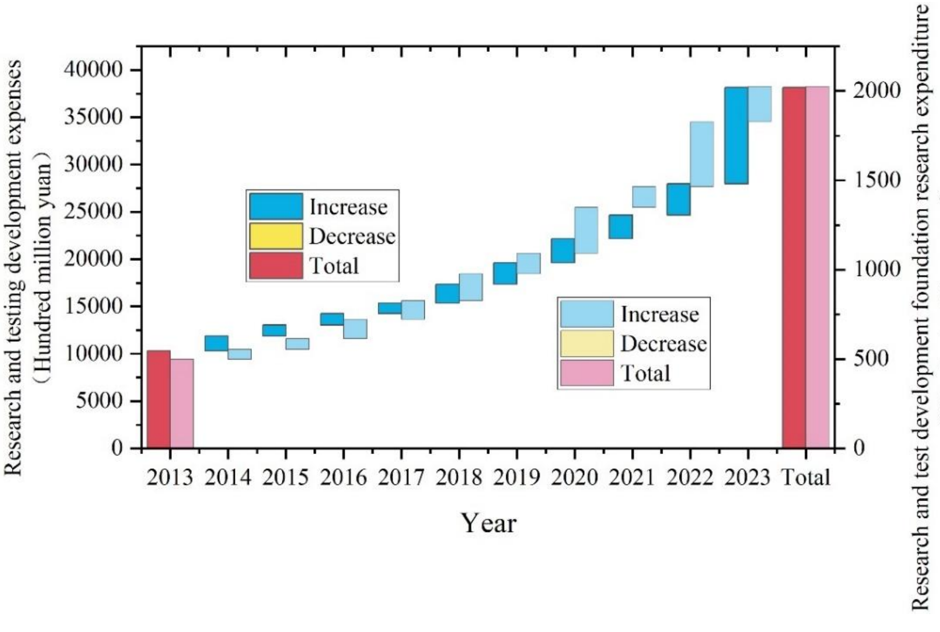

Figure 1. China's R&D expenditure situation from 2013 to 2023.

3.1.2. Research and Development Personnel

Figure 2 shows the full-time equivalent (FTE) of R&D personnel in China from 2013 to 2023. From the perspective of R&D personnel, the FTE of R&D personnel reached 631.648 million person-years in 2023, showing a significant upward trend. By the end of 2023, the full-time equivalent of R&D personnel engaged in basic research had reached 509,640 person-years, far exceeding the total from nine years ago, with an increase of over 200%.

Although the total number of personnel in both categories has been increasing annually, according to the "Industrial Artificial Intelligence Talent Research and Development Report (2023)," China currently faces an artificial intelligence talent shortage of approximately 24.2 million to 35.6 million people. The growing demand will further expand this shortage, and the mismatch between supply and demand for artificial intelligence talent will to some extent constrain the development of artificial intelligence technological innovation. In terms of talent structure, this manifests as "a large talent base but a lack of high-level talent."

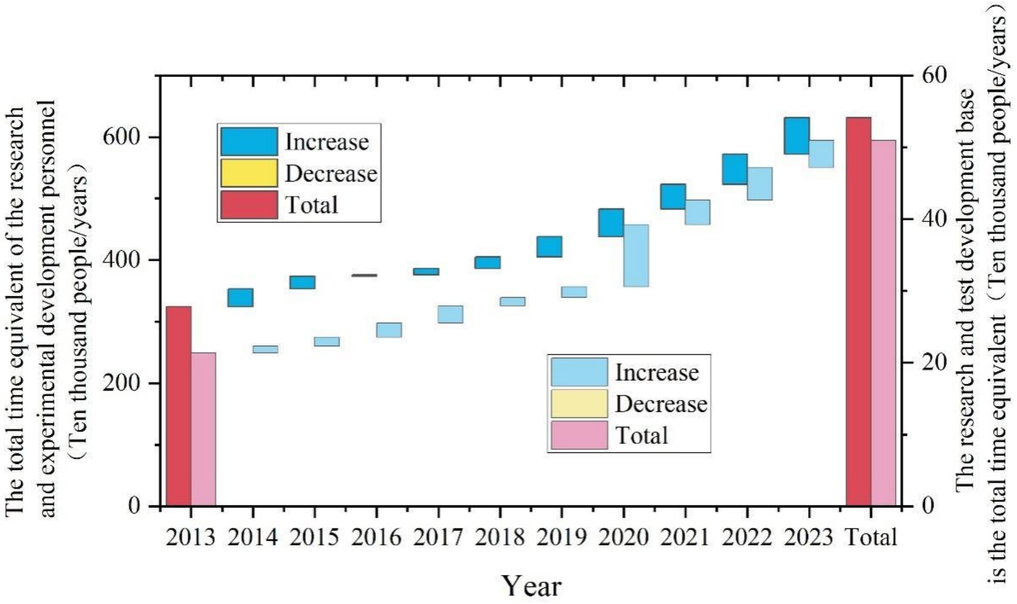

Figure 2. The total time of the R&D personnel in 2013-2023.

3.2. Innovation in Manufacturing Enterprises

3.2.1. Trends in regional AI technological innovation capabilities

In terms of both time and spatial distribution, artificial intelligence (AI) technological innovation exhibits distinct characteristics. By mapping the development levels of AI technological innovation across different years at both the national and regional levels, Figure 3 illustrates the trend in AI technological innovation levels across Chinese regions from 2013 to 2022. It can be observed that: First, the level of AI technological innovation in China has been steadily increasing from 2013 to 2022, with AI innovation indicators across cities showing a sustained upward trend. Second, from a regional perspective, AI technological innovation exhibits a spatially uneven distribution pattern. The eastern region has seen a gradual strengthening of its development momentum, while the central and western regions have relatively weaker development. This spatial evolutionary pattern has become increasingly evident. Additionally, when comparing the eastern, central, and western regions with the national level, the differences in AI technological innovation levels among prefecture-level cities have shown a trend of narrowing.

From 2013 to 2020, China's AI technological innovation transitioned from a low-speed development phase to a high-speed development phase, particularly since 2017, when AI technology experienced significant advancement. The vigorous promotion and implementation of the national big data strategy and cyberpower strategy have driven the flourishing development of the digital economy, thereby creating a favorable environment for AI technological innovation. 2017 marked a critical turning point, with significant changes in the level of AI technological innovation. It is evident that the development of AI technological innovation has been extremely rapid since 2017. The increasing activity and widespread application of AI technological innovation have strongly driven the continuous expansion of industrial intelligence and the deepening development of digital industrialization. The levels of intelligence, networking, and digitalization in society and the economy have significantly improved, propelling the digital economy into a phase of vigorous development. According to a report released by the China Academy of Information and Communications Technology, by the end of 2022, China's digital economy had reached 49.333 trillion yuan, representing a nominal year-on-year growth of 10.357%, which has been significantly higher than the nominal GDP growth rate for 11 consecutive years. The development momentum of digital industrialization and industrial intelligence has been strong, with the gap in penetration rates between the secondary and tertiary industries narrowing further, forming a new landscape of intelligent manufacturing that is conducive to the optimization of the industrial structure.

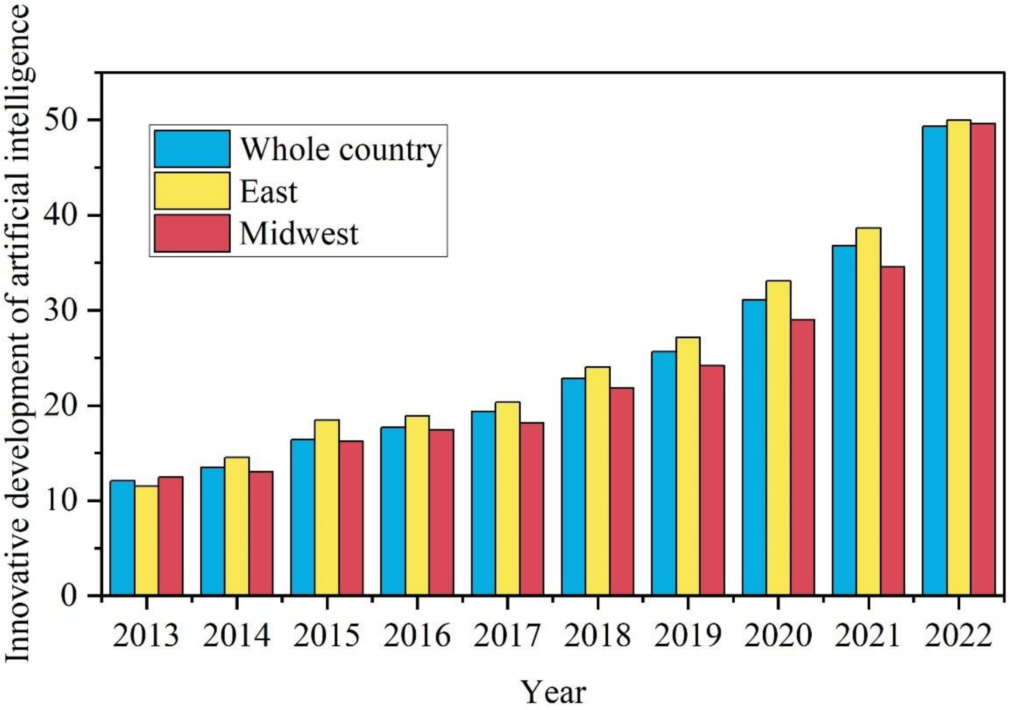

Figure 3. The development of AI technological innovation level from 2013 to 2022.

3.2.2. Manufacturing Innovation Capabilities

Based on the nine manufacturing sub-industries covered in this study, the manufacturing innovation capability index—defined as the proportion of intermediate inputs for manufacturing industry innovation services relative to total intermediate inputs—is used to reflect this. Table 1 presents the input-output data for manufacturing innovation services. The publication cycles for these data are irregular. Since the sample period for this study spans 2013–2023, the input-output table from 2013 is selected as the starting point. Overall, from 2013 to 2023, China's manufacturing innovation service level continued to improve, with the manufacturing innovation service rate index increasing by 1.651%. Additionally, whether in terms of input or output, the proportion of manufacturing innovation service input was higher than that of general manufacturing and showed an upward trend year by year.

Table 1. Manufacturing innovation services are invested in output.

Industry	2013	2015	2017	2018	2020	2023	Variation amplitude(%)
Food manufacturing and tobacco industry	8.286	4.088	6.748	8.654	8.745	8.065	-0.221
Textiles	5.635	2.398	4.398	7.168	7.415	7.265	1.63

Textile clothing shoe cap leather feather and its industry	9.531	3.755	6.531	10.265	10.636	11.048	1.517
Wood processing and furniture manufacturing	9.048	4.469	9.648	7.848	8.136	8.034	-1.014
Paper printing and cultural education	8.139	6.085	11.378	9.215	9.487	10.094	1.955
Oil processing, coking and nuclear fuel industry	4.388	2.655	9.084	6.215	6.469	7.768	3.38
Chemical industry	9.278	5.958	10.906	11.036	11.385	12.063	2.785
Non-metallic mineral industry	11.496	6.425	14.425	11.845	11.536	11.648	0.152
Metal smelting and rolling industry	6.294	5.215	9.825	8.533	8.468	8.536	2.242
Metal industry	6.358	5.698	11.748	9.425	9.536	9.748	3.39
General, special equipment manufacturing	8.625	7.048	12.498	10.985	11.425	11.829	3.204
Transportation equipment manufacturing	7.365	6.036	10.065	9.348	9.826	10.349	2.984
Electrical machinery and equipment manufacturing	8.965	5.798	9.648	8.846	9.068	9.485	0.52
Communication equipment, computer and his electronics manufacturing	9.515	7.748	10.098	8.863	9.165	9.625	0.11
Instrument and cultural office machinery manufacturing	8.348	8.065	12.948	9.425	9.798	10.064	1.716
Other manufacturing	8.425	6.765	9.965	10.164	10.164	10.498	2.073
Mean	8.106	5.513	9.995	9.24	9.454	9.757	1.651

4. Research design

4.1. Measurement Model and Research Hypotheses

To identify the impact of artificial intelligence on manufacturing innovation and its mechanism of action, this paper uses a two-way fixed effects econometric model to conduct empirical analysis at the two-digit industry level in China's manufacturing sector (i.e., two-digit code industries):

$$\ln Pat\_app_{i,t} = \alpha_0 + \alpha_1 \ln Robot_{i,t} + \alpha_2 X_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t} \tag{2}$$

In this context, the subscript i denotes the two-digit industry code for China's manufacturing sector, and the subscript t denotes the year. $\ln Pat\_app_{i,t}$ represents the innovation level of industry i in year t, while $\ln Robot_{i,t}$ denotes the industrial robot density of industry i in year t and serves as a proxy variable for artificial intelligence. $X_{i,t}$ denotes control variables, λ_i denotes the fixed effect of the two-digit industry code to control for industry heterogeneity, η_t denotes the fixed effect of the year to control for the impact of unobservable policy and technological shocks, and $\varepsilon_{i,t}$ denotes the residual disturbance term. This paper primarily focuses on the estimated coefficient α_1 of the core explanatory variable $\ln Robot_{i,t}$. If the sign of α_1 is significantly positive, it indicates that artificial intelligence, represented by industrial robots, has a significant promotional effect on innovation in China's manufacturing sector, thereby testing the research hypothesis H_1.

Regarding the heterogeneity of AI's impact on innovation, this paper introduces an interaction term between industry dummy variables and AI in the econometric model (2) to identify industry heterogeneity:

$$\begin{aligned}\ln Pat\_app_{i,t} = \beta_0 + \beta_1 \ln Robot_{i,t} + \beta_2 \ln Robot_{i,t} \\ \times ind_i + \beta_3 X_{i,t} + \lambda_i + \eta_t + \varepsilon_{i,t}\end{aligned} \tag{3}$$

Among these, ind_i denotes the industry dummy variable. If industry i belongs to a capital-intensive industry or a high-tech industry, then ind_i takes the value 1. If industry i belongs to a labor-intensive industry, then ind_i takes the value 0. The remaining variables are consistent with the econometric model (2). Here, the focus is on the estimated coefficient β_2 of the interaction term $\ln Robot_{i,t} \times ind_i$ between the core explanatory variable and the industry dummy variable. If the sign of β_2 is significantly positive, it indicates that, compared to labor-intensive industries, artificial intelligence has a greater promotional effect on innovation in capital-intensive industries and high-tech industries, thereby testing the research hypothesis H_2.

Additionally, to identify the heterogeneity of AI's impact on innovation by distinguishing between substantive innovation and strategic innovation, this paper replaces the dependent variable in econometric model (2) with $\ln Pat\_app_{i,t} = \left(\ln Inv_{i,t}, \ln Oth\_pat_{i,t}\right)$ in the econometric model (2). Here, $\ln Inv_{i,t}$ denotes the substantive innovation (logarithm of the number of invention patent applications) of industry i in year t, $\ln Oth\_pat_{i,t}$ denotes the strategic innovation of industry i in year t (the logarithm of the number of utility model and design patent applications), and the hypothesis H_3 is tested by comparing the marginal effects of artificial intelligence on substantive innovation and strategic innovation.

4.2. Sample Selection and Data Sources

The empirical data used in this paper is sourced from three main areas. First, the global industrial robot report published by the International Federation of Robotics (IFR). This organization conducts surveys of global robot manufacturers to generate panel data organized by “country-industry-year.” This paper utilizes the industrial robot installation data for China's two-digit industry codes in the manufacturing sector from 2013 to 2023. Second, the “China Science and Technology Statistical Yearbook.” This paper utilizes the patent application numbers for large-scale industrial enterprises by industry from 2013 to 2023, matches the two-digit industry codes and years with industrial robots, and forms "industry-year" panel data, with the two-digit industry codes ranging from 14 to 42 as the sample. Since China's manufacturing industry codes were adjusted in 2013 and 2017, this paper manually adjusted the industry codes based on the 2013 version of the "Classification of National Economic Activities." In the two-digit manufacturing industry codes, the plastic products industry and rubber products industry were separately reported before 2013, resulting in data for 28 industries after matching. After 2013, the plastic products industry and rubber products industry were combined into a single category, while the transportation equipment manufacturing industry was split into the automotive manufacturing industry and the railway, shipbuilding, aerospace, and other transportation equipment manufacturing industry, also yielding data for 28 industries after matching. Third, the "China Industrial Statistics Yearbook." This paper uses the manufacturing industry data for large-scale industrial enterprises by industry from 2013 to 2023, matching the two-digit industry codes with industrial robots to construct measurement indicators for control variables.

4.3. Variable Selection

(1) Dependent variable: Number of patent applications. This paper uses the total number of patent applications $(\ln Pat\_app_{i,t})$ as the dependent variable for benchmark regression analysis, and the total number of patent applications, the number of invention patent applications, and the number of utility model patent applications as the dependent variables for innovation heterogeneity analysis.

(2) Core explanatory variable: Artificial intelligence. This paper uses the density of industrial robots in the two-digit industry code of the manufacturing sector as a proxy variable for artificial intelligence. The IFR defines industrial robot density as the number of robots per 10,000 workers, with the robot stock estimated based on the IFR's statistics on the current installation volume of industrial robots by industry. The IFR's industry classification standards differ from those of the National Economic Activity Industry Classification (GB/T4754-2011). The specific matching methods are detailed below. This paper uses the perpetual inventory method to estimate the robot stock:

$$Robot_t = (1-\delta)Robot_{t-1} + Robot_{new,t} \tag{4}$$

Among these, $Robot_t$ denotes the current stock of robots, $Robot_{t-1}$ denotes the stock of robots in the previous period, $Robot_{new,t}$ denotes the number of new robots installed in the current period, and δ denotes the depreciation rate, which is set at 10%.

(3) Control variables: export intensity, foreign direct investment, financing constraints, and capital deepening. 1) Export intensity $(\ln Exp\_int)$ is measured by the proportion of export output value to total sales in the two-digit industry. This indicator reflects the export intensity of the industry's products, and export intensity has a positive promotional effect on innovation. 2) Foreign direct investment $(\ln Fdi)$ is measured as the proportion of total foreign investment in the two-digit industry sector relative to total assets. Due to the lack of industry-level statistics on foreign direct investment, this paper measures foreign direct investment as the proportion of Hong Kong, Macao, and Taiwan capital plus foreign capital relative to paid-in capital. An increase in foreign direct investment can enhance the innovation capabilities of Chinese enterprises. 3) Financing constraints $(\ln Fc)$ are measured by the industry's interest expenses. The higher the interest expenses, the stronger the industry's financing capacity, the lower the financing costs, and the fewer the financing constraints, which helps stimulate enterprises' enthusiasm for innovation and promote technological innovation. 4) Capital deepening $(\ln Asset)$ is measured by the industry's fixed assets. The higher the capital deepening, the larger the industry's asset scale, thereby having more funds available for R&D investment to enhance innovation levels.

4.4. Model Design

4.4.1. Basic regression model

The basic regression model in this paper is shown in Formula (5):

$$\begin{aligned} Patent_{i,t} &= \beta_0 + \beta_1 INTERL\_a_{i,t} + \beta_2 Controls_{i,t} \\ &\quad + \sum Industry + \sum Year + \varepsilon_{i,t} \end{aligned} \tag{5}$$

In this context, the subscript i and subscript t represent the individual firms in the sample and the year to which the sample belongs, respectively. The dependent variable $Patent$ in this paper represents innovation in manufacturing firms, specifically broken down into three quantitative indicators: total number of patent applications, number of invention patent applications, and number of utility model patent applications. The core explanatory variable for firms is firm intelligent transformation (INTEL_a), and Controls refers to the control variables mentioned earlier. Additionally, the model controls for industry and year.

4.4.2. Mechanism verification model

In order to examine the channels through which intelligent transformation influences innovation in manufacturing enterprises, the following model was constructed:

$$Mediator_{i,t} = \beta_0 + \beta_1 INTERL\_\ a_{i,t} + \beta_2 Controls_{i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{6}$$

$$Patent_{i,t} = \beta_0 + \beta_1 INTERL\_a_{i,t} + \beta_2 Mediator_{i,t} + \beta_3 Controls_{i,t} + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{7}$$

This model is a combined model for testing the mechanism of the impact of intelligent transformation on corporate innovation, where Mediator represents two mediating variables for testing the mechanism of the impact of intelligent transformation on corporate innovation. If the coefficient of INTEL in formula (6) is positive, it indicates that intelligent transformation is positively correlated with the mechanism variable. If the coefficient of INTEL in model (7) is significantly positive, it indicates that the mechanism variable has a mediating effect in the relationship between intelligent transformation and corporate innovation. Government subsidies provided by industrial policies can to some extent alleviate the innovation challenges faced by enterprises.

H4: The application of technologies such as artificial intelligence influences the innovation performance of manufacturing enterprises through the acquisition of government subsidies.

Table 2 provides a description of the main variables, where the explanatory variable Treat×Year is a dummy variable interaction term: if the firm belongs to the manufacturing sector that has adopted artificial intelligence technology (hereinafter referred to as an artificial intelligence firm), Treat takes the value of 1. If not, Treat takes the value of 0. For artificial intelligence firms, Year takes the value of 0 before 2015 and 1 afterward, while for non-artificial intelligence firms, Year takes the value of 0.

Table 2. Main variable specification.

Type	Symbol	Name
Explained variable	Pat	Number of patent applications
Explanatory variable	Treat×Year	Artificial intelligence
Mediating variable	Gov	Government subsidy
	Robot	Industrial robot
	Ind	Industry type
	Inv	Innovation strategy
Control variable	Exp	AExport intensity
	Fdi	Foreign direct investment
	Fc	Financing constraint
	Asset	Degree of capital deepening

5. The Impact of AI-driven Government Innovation Services on the Mechanism for Enhancing Manufacturing Innovation

5.1. Descriptive statistical analysis of key variables

Table 3 shows the descriptive statistics of the main variables. After collation, data from 350 listed manufacturing companies from 2013 to 2023 were obtained, including 150 companies in the artificial intelligence group and 200 companies in the non-artificial intelligence group, for a total of 3,145 observations. It can be observed that the mean value of the total number of invention patent applications (Pat) for enterprises is 2.148, with a standard deviation of 1.448, a minimum value of 0, and a maximum value of 7.294. This indicates that the overall number of invention patent applications for enterprises is at a relatively high level, but there are still significant differences in the number of patent applications among different manufacturing enterprises. The mean value of Treat×Year is 0.264, with a standard deviation of 0.426, indicating that the proportion of artificial intelligence companies in the sample period is lower than that of non-artificial intelligence companies.

Table 3. Descriptive statistics of major variables.

Variable name	Observed value	Mean	Standard deviation	Minimum value	Maximum value
Pat	3145	2.148	1.448	0	7.294
Treat×Year	3145	0.264	0.426	0	1
Gov	2636	5.945	1.165	2.348	9.812
Robot	2647	16.635	1.595	8.948	22.215
Ind	3145	0.154	0.348	-0.425	1.632
Inv	3145	0.566	0.164	0.248	0.852
Exp	3145	2.648	0.458	1.634	3.634
Fdi	3145	22.068	1.094	19.948	25.348
Fc	3145	0.384	0.198	0.049	0.865
Asset	3145	1.348	0.636	1.249	1.165

5.2. Regression Results and Analysis

This paper employs STATA 16.0 for empirical analysis, utilizing a difference-in-differences model to assess the impact of artificial intelligence (AI) technology adoption on the innovation performance of manufacturing firms from 2013 to 2023. The baseline regression results are presented in Table 4. Table 4 presents the regression results of Model (5), reporting the estimated results of the difference-in-differences model. As shown in the table, under the treatment variable Treat×Year, the net effect of artificial intelligence on enterprise innovation performance is reflected. In Column (1), the regression coefficient of the interaction term Treat×Year is 0.348, which is significantly positive at the 1% level, indicating that artificial intelligence technology significantly enhances the innovation performance of manufacturing enterprises at this time.

Column (2) adds relevant control variables at the firm level based on Column (1). The coefficient of the interaction term Treat×Year remains significantly positive at the 1% level, indicating that artificial intelligence technology plays a promotional role in enhancing the overall innovation performance of manufacturing firms, with a regression coefficient of 0.287. This demonstrates that there is a highly significant positive correlation between the application of artificial intelligence technology and the innovation performance of manufacturing firms.

Table 4. Double difference regression.

Variable	(1)	(2)
	Pat	Pat
Treat×Year	0.348***	0.287***
	(0.086)	(0.084)
Exp		0.618***
		(0.083)
Fdi		-0.148
		(0.248)
Fc		0.046**
		(0.016)
Asset		-0.569*
		(0.248)
Gov		-0.348
		(0.236)
_cons	1.548***	-11.885***

	(0.049)	(1.865)
Time-fixed effect	YES	YES
Individual fixed effect	YES	YES
N	3145	3145
r2_a	0.188	0.248

Note: (1) The robust standard errors are in parentheses: (2)***, **, and * respectively indicate significance at the 1%, 5%, and 10% levels, the same below.

5.3. Robustness testing

Based on the above, this paper conducts a robustness test of its core conclusions from the following aspects, as shown in Table 5.

(1) Replace the explanatory variable. The number of innovation patent applications filed by manufacturing enterprises ($\ln Total$) reflects the level of innovation of manufacturing enterprises to a certain extent. In the baseline regression of this paper, the total quantity is used as the measure. Empirical evidence shows that the development of artificial intelligence technology can indeed promote an increase in the total number of patent applications. To test the robustness of the results, this paper further distinguishes between patent categories, replacing them with two sub-variables: invention patents ($\ln \ln via$) and utility model patents ($\ln Umia$). The regression results for this part are shown in Table 5 Column (1) and Table 5 Column (2): The regression coefficients for the development of artificial intelligence technology on the two variables of invention patents and utility model patents are 0.082 and 0.042, respectively, which are statistically significant at the 1% level and show no significant difference from the benchmark regression results. This indicates that the results remain robust even after replacing the explanatory variables.

(2) Replace explanatory variables. Based on the "Big Data Industry Development Plan (2016–2020)", the "13th Five-Year National Science and Technology Innovation Plan", and relevant important news and meeting content, extract core terms related to artificial intelligence and count the number of search results. Add up the number of search results for the same city to obtain the total search volume. Finally, this indicator is log-transformed to serve as a measure of the level of artificial intelligence development at the city level. Replace the original model's core explanatory variable with this indicator, as shown in Column (3) of Table 5. The regression coefficient is 0.035, which is significant at the 5% level, and the results remain robust.

Table 5. Robustness test.

Variable	(1)	(2)	(3)
	InInvia	InUmia	InTotal
Treat×Year	0.082***	0.042***	
	(0.019)	(0.018)	
L.Treat×Year			0.035**
			(0.018)
Exp	-0.024	-0.025	-0.004
	(0.142)	(0.152)	(0.178)
Fdi	0.178*	0.089	0.078
	(0.093)	(0.093)	(0.105)
Fc	0.025	-0.025	-0.003
	(0.039)	(0.039)	(0.044)
Asset	-0.015	0.018	0.023
	(0.016)	(0.013)	(0.023)
_cons	-0.936	-0.078	-1.165
	(0.562)	(0.615)	(0.726)
Firm/Year	YES	YES	YES
N	3145	3145	3145

r2	0.048	0.018	0.039

5.4. Verification of the mechanism of action

5.4.1. Human Capital Effects

From the theoretical analysis above, it can be seen that the application of industrial robots in enterprises can encourage enterprises to hire higher-quality labor, promote enterprise innovation by improving the enterprise's labor structure and enhancing the skill level of its workforce. Therefore, this section uses a mediation effect model to explore whether the application of industrial robots further affects the level of enterprise innovation through its role in enhancing human capital. The empirical model is as follows:

$$\begin{aligned} inn_{ijt} &= \alpha_1 + \theta_1 \operatorname{int} ensity_{ijt} + \beta_1 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{8}$$

$$\begin{aligned} labor_{ijt} &= \alpha_2 + \theta_2 \operatorname{int} ensity_{ijt} + \beta_2 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{9}$$

$$\begin{aligned} inn_{ijt} &= \alpha_3 + \theta_3 \operatorname{int} ensity_{ijt} + \theta_4 labor + \beta_3 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{10}$$

Among these, the intermediate variable of human capital level was selected based on the number of employees with bachelor's degrees and master's degrees or above, which was then log-transformed to serve as a proxy variable for human capital level. Since employees' degrees generally do not change after they enter the workforce, employees with bachelor's degrees or above can represent the human capital level of an enterprise.

5.4.2. Knowledge spillover effect

The theoretical mechanism section explains the positive relationship between knowledge spillover effects and corporate R&D investment and innovation. The application of industrial robots will stimulate corporate demand for new technologies and knowledge, thereby promoting innovation. Therefore, this subsection uses a mediation effect model to explore whether the application of industrial robots further influences corporate innovation levels through its knowledge spillover effects. The empirical model is as follows:

$$\begin{aligned} inn_{ijt} &= \alpha_1 + \theta_1 \operatorname{int} ensity_{ijt} + \beta_1 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{11}$$

$$\begin{aligned} rd_{ijt} &= \alpha_2 + \theta_2 \operatorname{int} ensity_{ijt} + \beta_2 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{12}$$

$$\begin{aligned} inn_{ijt} &= \alpha_3 + \theta_3 \operatorname{int} ensity_{ijt} + \theta_4 rd_{ijt} \\ &\quad + \beta_3 X_{ijt} + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{13}$$

Among them, the number of R&D personnel is selected as the indicator of knowledge spillover effects, as it reflects the company's R&D intensity, i.e., the level of knowledge spillover effects.

5.4.3. Cost savings

The theoretical mechanism section explains the positive relationship between cost savings and corporate R&D investment and innovation. The application of industrial robots reduces corporate costs and increases productivity, allowing companies to retain surplus funds and promote innovation. Therefore, this section uses a mediation effect model to explore whether the application of industrial robots further influences corporate innovation levels through its cost savings effect. The empirical model is as follows:

$$\begin{aligned} inn_{ijt} &= \alpha_1 + \theta_1 \operatorname{int} ensity_{ijt} + \beta_1 X_{ijt} \\ &\quad + Firm + Industry + Year + u_{ijt} \end{aligned} \tag{14}$$

$$\begin{aligned} \cos t_{ijt} &= \alpha_2 + \theta_2 \operatorname{int} ensity_{ijt} + \beta_2 X_{ijt} \\ &+ Firm + Industry + Year + u_{ijt} \end{aligned} \tag{15}$$

$$\begin{aligned} inn_{ijt} &= \alpha_3 + \theta_3 \operatorname{int} ensity_{ijt} + \theta_4 \cos t + \beta_3 X_{ijt} \\ &+ Firm + Industry + Year + u_{ijt} \end{aligned} \tag{16}$$

Among these, the cost-saving effect of the mediator variable is represented by the ratio of sales expenses to main business revenue, i.e., the sales expense ratio, as it reflects the company's cost expenditure level to a certain extent.

Table 6 presents the regression results for the mediator effect, reporting the mediator effect (Interm) regression results of this study. Specifically, columns (1) and (2) of Table 6 show the regression results for the cost-saving effect, while columns (3) and (4) present the regression results for the knowledge spillover effect, and columns (5) and (6) present the regression results for the human capital effect.

As shown in Table 6 (1), the coefficient of artificial intelligence on the sales expense ratio is significantly negative at the 1% level, with a regression coefficient of -0.005. This indicates that the application of artificial intelligence can reduce the sales expense ratio, achieving a cost-saving effect, thereby freeing up more idle funds for technological innovations such as process improvements. Further observation of Column (2) in Table 6 shows that the sales expense ratio has a significant negative correlation with innovation in manufacturing enterprises, with the regression coefficient being significantly negative at the 1% level. This indicates that the higher the sales expense ratio of an enterprise, the lower the likelihood of the enterprise initiating innovation. Meanwhile, the coefficient for the impact of artificial intelligence on manufacturing innovation is significantly positive, indicating that the cost-saving effect plays a partial mediating role in the process of artificial intelligence promoting the innovation level of manufacturing enterprises. In summary, the application of artificial intelligence promotes innovation in manufacturing enterprises by reducing corporate costs.

As shown in Column (3) of Table 6, the regression coefficient for the impact of AI on the number of R&D personnel is 1.648, which is significantly positive at the 1% level. This indicates that the application of AI can increase the number of R&D personnel in enterprises, achieve knowledge spillover effects, and thereby enable more employees to participate in technological innovations such as process improvements. Further observation of Column (4) in Table 6 shows that the number of R&D personnel has a significant positive correlation with innovation in manufacturing enterprises, indicating that the more R&D personnel an enterprise has, the more conducive it is to the enterprise initiating innovation. Furthermore, the coefficient for the effect of AI on manufacturing innovation is significantly positive, indicating that the knowledge spillover effect plays a partial mediating role in the process of AI promoting the innovation level of manufacturing enterprises. In summary, the application of AI technology promotes the hiring of more R&D personnel through the knowledge spillover effect, thereby converting into innovation outcomes in corporate R&D activities.

As shown in column (5) of Table 6, the coefficient of the human capital effect of artificial intelligence (0.096) is significantly positive at the 1% level, indicating that the application of artificial intelligence can increase the number of employees with a bachelor's degree or higher, thereby achieving a human capital effect and enabling more highly skilled employees to participate in technological innovations such as process improvements. Further observation of Table 6 column (6) shows that the human capital effect has a significant positive correlation with innovation in manufacturing enterprises (regression coefficient of 0.031, significant at the 1% level), indicating that the more highly skilled personnel a company has, the more conducive it is to initiating process innovation. Since the coefficient for AI's impact on manufacturing innovation is significantly positive, this suggests that the human capital effect plays a partial mediating role in the process by which AI promotes innovation levels in manufacturing enterprises. In summary, the application of artificial intelligence technology promotes the accumulation of high-quality talent through the human capital effect, thereby driving more innovation. Therefore, hypothesis H1 is supported.

Table 6. The mediation effect returns.

Variable	Cost-saving effect		Knowledge spillover effect		Human capital effect	
	(1)	(2)	(3)	(4)	(5)	(6)
	Interm	Inn	Interm	Inn	Interm	Inn
Treat×Year	-0.005***	0.034***	1.648***	0.024**	0.096***	0.031***
	(-7.654)	(3.725)	(21.631)	(2.348)	(3.648)	(3.715)
Interm		-0.248***		0.005***		0.019***
		(-2.648)		(8.618)		(5.158)

Control variable	YES	YES	YES	YES	YES	YES
_cons	0.148***	1.485***	55.945***	0.848**	-4.648***	1.448***
	(6.048)	(4.425)	(23.198)	(2.536)	(-6.068)	(4.425)
Industry	YES	YES	YES	YES	YES	YES
Firm	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	3145	3145	3145	3145	3145	3145
F value	68.485	19.469	771.696	28.352	218.636	22.125
Adj.r2	0.869	0.615	0.665	0.669	0.812	0.648

The specific results of the mediation effect test for industry type, innovation strategy, and government subsidies are shown in Table 7.

Column (1) and Column (2) present the results of the industry type test. In Column (1), the dependent variable is the industry type of the firm (Ind), and the coefficient of $Treat \times Year$ indicates that the implementation of artificial intelligence technology can optimize the industry type of the firm, leading to the hiring of more highly skilled employees. Column (2) has the dependent variable of firm innovation performance Pat, with a regression coefficient of 0.186. The coefficient of $Treat{\times}Year$ remains significantly positive at the 5% level, and the coefficient of Ind (0.135) is significantly positive at the 10% level, indicating that the optimization of a firm's industry type positively impacts its innovation performance. Therefore, the implementation of artificial intelligence technology enhances corporate innovation performance by optimizing the industry type of the enterprise, supporting hypothesis H2.

Columns (3) and (4) present the results of the internal innovation strategy test. In column (3), the dependent variable is innovation strategy Inv, with a regression coefficient of 0.195. The coefficient of $Treat{\times}Year$ is significantly positive at the 5% level, indicating that the introduction of AI technology can enhance the innovation strategies adopted by firms. In column (4) has innovation performance Pat as the dependent variable, and the coefficient of $Treat{\times}Year$ is also significantly positive at the 5% level, indicating that improvements in innovation strategy positively influence innovation performance. Therefore, the application of artificial intelligence technology can promote corporate innovation performance through internal innovation strategies, supporting hypothesis H3.

Columns (5) and (6) present the results of testing external government subsidies. In column (5), the dependent variable is government subsidies (Gov), $Treat \times Year$ coefficient at the 5% level. The introduction of technology can increase the government subsidies received by the company. Column (6) has the explained variable of manufacturing company innovation performance Pat (0.185), The coefficient of $Treat \times Year$ at the 5% level is also significantly positive, indicating that an increase in government subsidies can positively influence corporate innovation performance. Therefore, the application of artificial intelligence technology can promote corporate innovation performance by increasing government subsidies, supporting hypothesis H4.

Table 7. Industry type, innovation strategy, government subsidy.

Variable	Industry type		Innovation strategy		Government subsidy	
	(1)	(2)	(3)	(4)	(5)	(6)
	Ind	Pat	Inv	Pat	Gov	Pat
Treat×Year	0.148***	0.186**	0.195***	0.197**	0.156**	0.185**
	(0.049)	(0.089)	(0.096)	(0.086)	(0.085)	(0.073)
Gov						0.056**
						(0.024)
Robot	0.166***	0.542***	0.936***	0.536***	0.897***	0.769***
	(0.045)	(0.096)	(0.165)	(0.096)	(0.166)	(0.095)
Ind		0.135*				
		(0.058)				
Inv				0.158**		
				(0.064)		
Exp	0.005	0.038**	0.025	0.024	0.037**	0.088**
	(0.015)	(0.018)	(0.015)	(0.015)	(0.019)	(0.168)
Fdi	-0.458***	-0.569*	-0.348	-0.398	-0.648**	-0.365**
	(0.136)	(0.325)	(0.348)	(0.315)	(0.365)	(0.348)
Fc	0.135	-0.185	0.185	0.158	0.048	0.148
	(0.159)	(0.345)	(0.038)	(0.396)	(0.398)	(0.198)

Asset	0.086	-0.518**	0.398	0.318	-0.518**	0.348**
	(0.128)	(0.248)	(0.259)	(0.298)	(0.248)	(0.198)
_cons	-7.248***	-9.945***	-4.458*	-4.689	-10.869***	-8.369***
	(1.188)	(2.036)	(2.248)	(2.269)	(2.098)	(2.087)

6. Conclusion and Outlook

6.1. Conclusion

This paper defines the concepts of artificial intelligence in manufacturing and manufacturing innovation capabilities, and conducts research on the current status of AI development and manufacturing enterprise innovation based on the theoretical foundation of innovation-driven and endogenous growth. Through the design of a research hypothesis model, it analyzes the impact of government services on manufacturing innovation mechanisms under AI technology.

Data from 2013 to 2023 were compiled, and descriptive statistical analysis was conducted on the main variables of the model. The mean, standard deviation, minimum, and maximum values of the total number of patent applications (Pat) were 2.148, 1.448, 0, and 7.294, respectively, indicating that the overall level of patent applications by enterprises is relatively high.

A difference-in-differences model was employed to measure the impact of AI technology adoption on the innovation performance of manufacturing enterprises. The regression coefficient of the explanatory variable AI technology on the performance of manufacturing enterprises was 0.348, which was significantly positive at the 1% level, indicating that AI technology significantly enhances the innovation performance of manufacturing enterprises.

Based on the above research foundation, a robustness test was conducted on the core conclusions. The regression coefficients for the development of artificial intelligence technology on the two variables of invention patents and utility model patents were 0.082 and 0.042, respectively, and were significant at the 1% level, indicating that the results remain robust after replacing the explanatory variables, and the regression results have a high degree of reliability.

6.2. Outlook

The limitations of this study primarily manifest in two aspects. First, in terms of sample selection, this paper utilizes China's manufacturing industry codes as the research sample. This selection is based on two considerations: first, the difficulty in obtaining annual report data from private enterprises; second, the practical challenges in conducting intelligent level measurements for all samples. Therefore, the selection of samples has certain limitations. Second, regarding the study of the impact pathways of artificial intelligence on the innovation performance of manufacturing enterprises, due to the comprehensive and complex impact of intelligent transformation on enterprise development, the mechanisms and pathways through which artificial intelligence levels influence enterprise innovation performance are equally complex. Although this paper analyzed the mediating roles of government subsidies and industry type, as well as the moderating role of redundant resources, a deeper understanding of the mechanisms through which enterprise intelligentization levels influence innovation performance remains an area for future research. In particular, the moderating role of resources remains unclear and requires further exploration. These research limitations provide direction for future exploration and are expected to lead to more in-depth studies in the future.

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