

How Artificial Intelligence Affects Green Innovation—— Evidence Based on Listed Manufacturing Companies in China

Abstract: With the rapid development of artificial intelligence (AI) technology, manufacturing enterprises are gradually entering the wave of digital and intelligent transformation. However, whether AI technology can empower corporate green innovation and the underlying mechanisms of their interaction remain unclear. Based on panel data of listed manufacturing companies in Shanghai and Shenzhen A-shares from 2010 to 2023, this paper employs a double fixed-effects model to explore how AI influences corporate green innovation and analyze the mediating mechanisms of AI's empowerment of green innovation. The findings reveal a nonlinear "U-shaped" relationship between AI and corporate green innovation, where AI first inhibits and then promotes green innovation. Absorptive capacity and human capital play "U-shaped" mediating roles in the relationship between AI and green innovation. The "U-shaped" effect of AI on green innovation is significant in small-scale enterprises, non-state-owned enterprises, enterprises with low competition intensity, and high-tech enterprises. Media attention positively moderates the "U-shaped" relationship between AI and corporate green innovation. These conclusions enrich the research on the nonlinear relationship between AI and green innovation and contribute to revealing how AI can empower corporate green innovation.

Keywords: Artificial Intelligence; Green Innovation; Absorptive Capacity; Human Capital; Media Attention

1.Introduction

In the context of rapid globalization and economic expansion, environmental challenges—especially global warming—pose a severe test to human society. As one of the world's leading energy consumers, China has demonstrated its responsibility as a major power by announcing its "dual carbon goals" in September 2020: committing to achieving a carbon peak by 2030 and striving for carbon neutrality by 2060. Green innovation, integrating the two core concepts of "green development" and "innovative development" from the new development philosophy, serves as a critical pathway to implement this vision. Its aim is to harmonize economic growth with environmental protection, driving high-quality development of China's economy. Green innovation represents one of the most significant determinants influencing green development (Feng & Chen, 2018; Liao et al., 2022). With the rapid advancement of technology, continuous deepening of research and development in big data, artificial intelligence (AI), and active promotion of the "AI+" initiative, AI—as a key driver of the new round of scientific and technological revolution and industrial transformation—is profoundly reshaping global economic landscapes and industrial transformation directions (Aghion et al., 2017).

Previous studies on green innovation have primarily focused on corporate governance (Amore & Bennedsen, 2016), industrial policy (Zhu & Tan, 2022), and environmental regulations (Lian et al., 2022). Existing research on the impact of artificial intelligence (AI) on green innovation has approached the topic from diverse perspectives. Hussain et al. (2024) highlighted the positive influence of AI on green innovation. Lee et al. (2022), through analyzing the application of industrial robots, revealed that AI significantly promotes global manufacturing green technological innovation via the mediating role of green R&D investment and the moderating effect of environmental regulation. From the perspective of labor costs and human capital structure, Gan et al. (2023) found that the promotional effect of industrial robots on green innovation is more pronounced under strict environmental regulations, in high-tech industries, among firms with high R&D investment, and in non-state-owned enterprises. Liang et al. (2024) further demonstrated that industrial robot adoption enhances corporate green innovation by improving production efficiency, human capital, and environmental governance, thereby increasing both the quality and scale of green innovation. Wang et al. (2023) compared the differences in AI's role in promoting green innovation between developed and developing countries, while Feng et al. (2024) found that AI has a stronger impact on green innovation in non-state-owned enterprises and high-tech firms. These studies primarily focus on the promotional effects of AI on green innovation, yet few have explored the nonlinear impact of artificial intelligence (AI) on green innovation. Therefore, delving into the influence of AI on green innovation and its underlying mechanisms holds significant research value.

Our research contributes to three branches of literature. First, Existing studies on the impact of AI on corporate green innovation have mainly focused on linear relationships. This paper instead explores the "U-shaped" characteristics of AI's nonlinear influence on green innovation, aiming to further enrich and deepen the understanding of factors shaping AI's role in corporate green innovation and provide new perspectives for related research. Second, Mediating Mechanisms: From the perspectives of absorptive capacity and human capital, this paper explores the mechanisms through which AI empowers corporate green innovation. By analyzing both theoretical and empirical dimensions, it investigates whether and how AI technologies can facilitate green

innovation in manufacturing enterprises. Third, This study further examines how media attention influences the relationship between AI and corporate green innovation, explaining how external environmental factors moderate AI's effects on green innovation.

2. Literature review

2.1. The Impact of Artificial Intelligence on Corporate Green Innovation

According to Schumpeter's innovation theory, in its early stages, artificial intelligence (AI) acts as a disruptive technology that causes destructive impacts on the existing economic structure and production methods. In the field of green innovation, this destructiveness manifests as a shock to traditional green technologies and methods, leading to the elimination of outdated models unable to adapt to new technologies.

First, during the initial introduction of new technologies, due to limited understanding and application capabilities of AI among market participants, this information asymmetry suppresses the potential for green innovation. Firms struggle to accurately assess the green innovation benefits of investing in AI technology (Gregori & Holzmann, 2020).

Second, in the early phase of AI adoption, firms invest substantial capital in 智能化转型 (smart transformation), which may trigger a "crowding-out effect." This diverts funds away from green technological progress (Zhao et al., 2022). Meanwhile, firms face challenges such as information overload and cybersecurity issues (Brynjolfsson, 2022), which substantially increase the cost of information processing (Yin & Yu, 2022). This exacerbates financial pressures, 挤占 green innovation budgets, and inhibits improvements in corporate green innovation levels.

Finally, the development and application of AI technology may be constrained by existing technological paradigms, favoring traditional, non-green production and consumption patterns. Green innovation typically requires a long cycle to generate economic returns. Under the dual pressures of short-term cost increases and uncertain long-term benefits, AI adoption temporarily suppresses green innovation development (Petroni et al., 2019).

As AI technology gradually evolves, its potential is increasingly recognized and harnessed, with AI being reconfigured and applied to green innovation (Zhong & Song, 2025). First, AI can complete tasks faster, reducing operational time of machinery and equipment, thereby lowering resource consumption and environmental impact (Liang et al., 2024). This decreases firms' marginal production costs, increases profits, and raises internal investment in green innovation (Aghion et al., 2018; Dixon et al., 2021), providing robust financial support for green innovation. Second, similar to traditional innovation activities, green innovation requires substantial R&D investment with high risks. AI enables firms to rapidly access consumer preferences and environmental policies, helping identify new opportunities and mitigate risks and costs during green technological innovation (Rajagopal et al., 2022). Finally, AI technology collects, stores, and intelligently analyzes information, optimizing processing to achieve precise matching between information supply and demand. This alleviates information asymmetry, reducing the difficulty of acquiring new technologies and seeking partners, thus enabling firms to advance green innovation activities more efficiently (Su et al., 2022).

Overall, during the early stage of AI technology development, due to resource allocation constraints, firms often channel substantial technological innovation funds into R&D and applications of cutting-edge technologies like AI. This crowds out green innovation budgets to some extent, thereby temporarily inhibiting firms' green innovation capabilities. However, as AI matures

and becomes widely adopted, firms begin to recognize the importance of sustainable development. Consequently, they increasingly focus on integrating AI with green innovation, which enhances their green innovation capabilities and outputs, aiming to achieve a win-win situation for economic and environmental benefits. Based on the above analysis, this paper proposes the hypothesis:

H1: Artificial intelligence and enterprise green innovation has non-linear characteristics, showing a “U-shaped” relationship of inhibition and then promotion.

2.2. Role mechanism of the impact of artificial intelligence on corporate green innovation

2.2.1. Absorptive capacity mechanism of action

Absorptive capacity refers to a firm's ability to identify, acquire, integrate, and utilize external information to enhance its innovation capabilities and competitiveness (Cohen & Levinthal, 1990). In the early stage of AI technology adoption, absorptive capacity may temporarily decline. Firms require time to adjust operational processes, train employees, and integrate systems, which can lead to short-term operational inefficiencies and resource misallocation (Brynjolfsson et al., 2019). Additionally, the uncertainty of new technologies and disruptions to existing business models may cause firms to hesitate in applying AI.

However, as firms deepen their understanding and effective use of AI, the technology begins to positively impact absorptive capacity. AI can automate and intelligently process vast amounts of data, helping firms extract valuable insights from big data to rapidly identify market trends, customer needs, and potential risks. This improves the speed and quality of decision-making (Jarrahi, 2018). With advancements in AI, traditional information exchange models are innovated: information barriers between departments are broken, data centralization and sharing are achieved, and firms gain broader access to external resources (Joseph et al., 2024). By synthesizing external knowledge and fostering internal knowledge innovation, firms can reallocate resources and strengthen absorptive capacity (Gao et al., 2025). Thus, as AI technology evolves, corporate absorptive capacity may first decline and then rise, forming a "U-shaped" nonlinear relationship.

Absorptive capacity theory posits that external knowledge serves as a critical driver of corporate innovation. It not only enriches firms' existing knowledge stock, enhances their ability to identify potential opportunities and threats, but also provides organizations with new ideas and creativity. By effectively acquiring, absorbing, transforming, and applying external knowledge, firms can accelerate R&D processes, reshape innovation models, and optimize internal resource structures, thereby fostering product and process innovation (Wu et al., 2024). Absorptive capacity significantly promotes corporate green innovation performance (Aboelmaged & Hashem, 2019). Firms integrate environmentally friendly concepts and methods into product development and service design through absorbing external knowledge and technology, thereby driving green innovation. Albort-Moran et al. (2018) found that innovative organizations leverage absorptive capacity to convert external knowledge into internal innovation resources, developing new products, services, or improved processes and enhancing their green innovation outcomes. Based on the above analysis, this paper proposes the hypothesis:

H2: Artificial intelligence has a “U-shaped” relationship on green innovation by affecting the absorptive capacity of enterprises.

2.2.2. Mechanism of the role of human capital

During the development of AI technology, on the one hand, AI exerts a substitution effect on labor. Advances in AI enable machines to take over tasks previously performed by humans, which may lead to the replacement of low-skilled and unskilled workers by automation (Ramos et al., 2022;

Jetha et al., 2023). These workers may also face declining labor income (Autor & Salomons, 2018). Furthermore, technological progress increases the organic composition of capital and relative surplus population. Newly formed capital absorbs fewer workers during capital accumulation, leading to technological unemployment (Shen & Zhang, 2024).

On the other hand, AI technology has a creation effect on labor. As a key driver of the Fourth Industrial Revolution, AI is reshaping labor market structures (Chen, 2023). While low-skill jobs may be automated, new employment opportunities continuously emerge (Polak, 2021). By enhancing firm productivity, AI incentivizes firms to expand production scales, thereby increasing labor demand (Johnson et al., 2021). Additionally, AI, as a skill-biased technological advance, raises firms' demand for high-skilled labor while reducing demand for low-skilled labor (Wang et al., 2024). To avoid elimination in fierce market competition, low- and medium-skilled workers face urgent needs to adapt to the new technological environment by upgrading their skills and acquiring new knowledge to enhance competitiveness (Morandini et al., 2023). Thus, as AI technology evolves, corporate human capital levels may first decline and then rise, forming a "U-shaped" nonlinear relationship.

The efficiency and capability of corporate green innovation rely heavily on human capital, particularly the creativity of R&D personnel (Singh et al., 2020). R&D staff proficient in AI technology demonstrate stronger innovative potential compared to general skilled human capital. They not only improve resource utilization but also drive innovation in production materials and skills, which is critical for advancing technological R&D and green innovation. A firm's green innovation capability largely depends on the green-related knowledge, technologies, and competencies embedded in its human capital. These introduce new concepts, technologies, and methods to the organization. As human capital structures adjust and upgrade, knowledge and skill spillovers accelerate, enhancing corporate green innovation efficiency. Based on the above analysis, this paper proposes the hypothesis:

H3: Artificial intelligence presents a “U-shaped” relationship by affecting the human capital level of enterprises, and then its impact on green innovation.

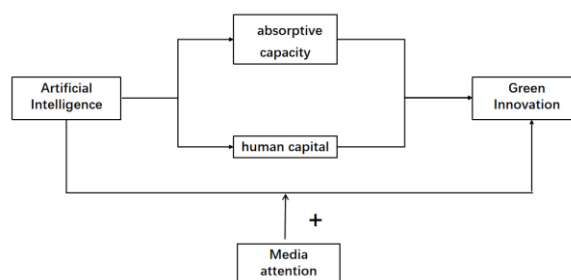


Figure 1: The Mechanism of AI on Enterprises' Green Innovation

3. Data and variables

3.1. Sample selection

This article selects listed companies in the manufacturing industry (classified according to the 2012 version of the industry classification for listed companies) of Shanghai and Shenzhen A-shares from 2010 to 2023 as the sample, including a total of 2,602 enterprises and 21,018 observation values. A series of data processing is carried out: the data of ST, *ST, and PT enterprises are deleted; enterprises with severely missing data are excluded; in order to reduce the impact of extreme values, bilateral winsorization at the 1% quantile is performed on all continuous variables. The data of this

article are sourced from the China Stock Market & Accounting Research Database (CSMAR), the annual reports of listed companies (CNINFO) and the China Research Data Services Platform (CNRDS).

3.2. Variable Definition and Measurement

3.2.1. Core Explanatory variables

The level of enterprise artificial intelligence (Int). Drawing on the measurement method of Song et al. (2025), the annual reports of listed manufacturing companies are utilized to establish a keyword library related to the enterprise's intelligent transformation. However, this processing method is not precise enough for the quantification of intelligent transformation. Therefore, on this basis, relevant policy documents on intelligent transformation are screened to construct a corpus. The method of "seed words + Word2Vec" is adopted to enrich the selection of keywords. Finally, 145 keywords related to intelligent transformation are obtained. Python is used to extract these keywords from the annual reports for text analysis and the processing of negative keywords. The intelligent transformation indicator is the total number of keywords related to intelligent transformation in the annual report of a manufacturing enterprise in the current year, and it is measured as follows: $Int = \ln(1 + \text{total number of keywords})$.

3.2.2. Core Explained Variables

The level of enterprise green innovation (GI). Patent data is an important indicator for measuring the innovation effectiveness of enterprises, and it can quickly reflect the innovation output of enterprises. Most of the current research scholars conduct analysis based on the number of green patent applications or authorizations as a measurement method. The patent application process may include some invalid applications, while patented technologies that have been authorized usually mean higher quality standards. The number of authorized patents can more accurately reflect the enterprise's innovation willingness and practical capabilities in the field of green technologies. In addition, the number of patent applications may be affected by the strategic behaviors of enterprises to meet regulatory requirements. For example, innovation activities carried out to obtain subsidies or tax exemptions do not truly reflect the enterprise's technological level. Therefore, in this study, the number of authorized green patents of enterprises is selected as a proxy variable. The specific measurement method refers to (Zhong & Song, 2025), $GI = \ln(1 + \text{the number of obtained green invention patents} + \text{the number of obtained green utility model patents})$. In the robustness test, the number of patent applications is selected as the proxy variable for the level of enterprise green innovation.

3.3.3. Control variables

Referring to the research of Liu et al. (2025), the influencing factors that may affect the level of enterprise green innovation have been controlled. The main control variables at the enterprise level include the debt-to-asset ratio (Lev), return on assets (Roa), operating cash flow (Cf), enterprise age (lnage), enterprise nature (soe), concentration ratio of the top ten shareholders (Top10), and enterprise size (size). At the same time, considering the control variables at the city level, the level of economic development (lngdp) and the degree of openness (open) are selected. Table 1 presents the descriptive statistics of the variables.

Table 1 Definitions of the main variables.

Variable	Symbol	Definition
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Explained	GI	ln(1 + green invention patents granted + green utility model patents granted)
Explanatory	Int	ln(1+total number of keywords)
Control	Lev	Ratio of total liabilities to total assets
	Cf	Operating cash flow to beginning total assets ratio
	lnage	Ln (year of observation - years on the market)
	size	Ln(Number of employees)
	Top10	Shareholding ratio of top ten shareholders
	Roa	Ratio of net profit to total assets
	soe	State-owned = 1 Non-state-owned = 0
	lngdp	GDP per capita in prefecture-level cities
	open	Foreign direct investment as a share of regional GDP

3.3. Model design

In order to test the research hypotheses, this paper sets the following model:

$$GI_{it} = \alpha_0 + \alpha_1 Int_{it} + \alpha_2 Int_{it}^2 + \sum \alpha_k controls_{it} + firm + year + \varepsilon_{it} \quad (1)$$

In Model (1), *i* represents a listed manufacturing enterprise, and *t* represents the year. The level of green innovation is denoted by *GI*, and the level of artificial intelligence is denoted by *Int*. To control for other potential influences, the model incorporates a series of control variables (*controls_{it}*) and takes into account the fixed effects of both the enterprise individual and time. In this model, α_1 and α_2 are the coefficients of primary concern in this article, representing the impact of artificial intelligence on green innovation. If the coefficient α_1 is significantly negative and the coefficient α_2 is significantly positive, it indicates that artificial intelligence has a non-linear characteristic with respect to green innovation, exhibiting a "U"-shaped relationship of first inhibition and then promotion, and thus Hypothesis 1 holds.

4. Results

4.1. Descriptive statistical analysis

Table 2 reports the statistical descriptions of the main and control variables. In our sample, Green Innovation (*GI*) has a maximum value of 3.367, a minimum value of 0, and a standard deviation of 0.724. This finding suggests that the level of green innovation is inconsistent across listed firms in China. Artificial Intelligence (*Int*) has a mean value of 5.283 and a standard deviation of 0.571, which suggests that the level of artificial intelligence varies greatly among firms.

Table 2 Statistical description

Variable	Obs	Mean	Std. Dev	Min	Max
GI	21018	0.358	0.724	0.000	3.367

Int	21018	5.283	0.571	2.996	6.822
Lev	21018	0.370	0.187	0.008	1.564
Cf	21018	0.053	0.069	-0.647	0.839
Inage	21018	1.840	0.943	0.000	3.332
size	21018	7.673	1.149	4.754	10.773
Top10	21018	59.514	14.768	25.260	95.406
Roa	21018	0.048	0.057	-0.171	0.277
soe	21018	0.253	0.435	0.000	1.000
Ingdp	21018	11.470	0.513	10.004	12.223
open	21018	0.005	0.006	-0.010	0.031

4.2. Baseline regression results

Table 3 shows the regression results based on Model (1). Column (1) only includes the first-degree term and the squared term of the explanatory variable in the regression. Column (2) fixes the individual and year effects on this basis. Column (3) includes all control variables in the regression but does not fix the individual and year effects. Column (4) adds the first-degree term and the second-degree term of the explanatory variable, control variables, and individual and time fixed effects to the model. It can be found that regardless of which regression result it is, both show that the first-degree term of artificial intelligence is significantly negative at the 1% significance level, while the second-degree term of artificial intelligence is significantly positive at the 1% significance level. This indicates that the impact between artificial intelligence and green innovation presents non-linear characteristics, showing a "U"-shaped relationship of first inhibition and then promotion. The above regression results show that when the development level of artificial intelligence is low, it inhibits the level of green innovation, but when the development level of artificial intelligence is high, it promotes the level of green innovation. Therefore, Hypothesis H1 is confirmed.

Table 3 Baseline regression results.

Variable	(1)	(2)	(3)	(4)
	GI	GI	GI	GI
Int	-0.507*** (0.105)	-0.387*** (0.088)	-0.356*** (0.101)	-0.272*** (0.088)
Int^2	0.068*** (0.010)	0.038*** (0.009)	0.049*** (0.010)	0.025*** (0.009)
Lev			0.463*** (0.033)	-0.005 (0.038)
Cf			-0.232***	-0.062

			(0.081)	(0.062)
Inage			-0.093*** (0.007)	-0.001 (0.011)
size			0.124*** (0.007)	0.078*** (0.011)
Top10			-0.002*** (0.000)	-0.000 (0.001)
Roa			0.178* (0.100)	-0.205** (0.081)
soe			0.068*** (0.013)	-0.028 (0.026)
lngdp			0.081*** (0.009)	-0.045** (0.020)
open			4.767*** (0.869)	1.647** (0.762)
constant	1.109*** (0.272)	1.323*** (0.218)	-0.920*** (0.278)	1.018*** (0.333)
Year	No	Yes	No	Yes
Company	No	Yes	No	Yes
N	21018	21018	21018	21018
R2	0.030	0.652	0.095	0.654

4.2. Robustness test

4.2.1. Utest test

Based on the research of Haans et al. (2016), this paper further validates the "U"-shaped relationship between artificial intelligence and green innovation. The results of the Utest are presented in Table 4. The range of the artificial intelligence level is (2.996, 6.822), and the turning point is 5.266, which falls within this range. The slope of the interval to the left of the turning point is -0.120, which is significant at the 1% significance level, and the slope of the interval to the right of the turning point is 0.074, also significant at the 1% significance level. Figure 2 depicts the "U"-shaped relationship between artificial intelligence and green innovation, further validating Hypothesis H1.

Table 4 Utest test.

Variable	Min	Max
Int	2.996	6.822
Slope	-0.120	0.074
T—value	-3.363	1.947
P-value	0.000	0.026
Overall p—value	0.026	

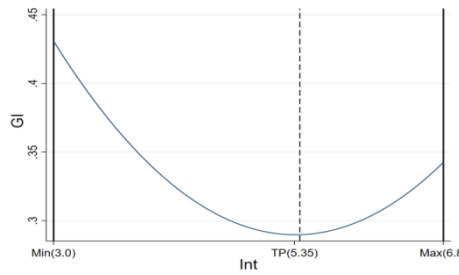


Fig. 2 U-shaped relationship between artificial intelligence and green innovation

4.2.2. Replacement of explanatory and explained variables

According to the research of Quan et al. (2021), the measurement method of green innovation is changed to taking the natural logarithm of the sum of the number of green invention and utility model patent applications of enterprises plus one (GI1). Re-regression is carried out according to Model (1), and the obtained regression results are shown in column (1) of Table 5. The relationship between artificial intelligence and enterprises' green innovation still shows a "U"-shaped relationship of first inhibition and then promotion. The measurement method of artificial intelligence is changed to measure it by the proportion of the total number of artificial intelligence keywords of manufacturing enterprises in the annual report of the current year to the total number of keyword occurrences of enterprises in the same industry in the same year. The obtained regression results are shown in column (2) of Table 5. The coefficient of the first-degree term of artificial intelligence is significantly negative at the 5% significance level, while the coefficient of the squared term of artificial intelligence is significantly positive at the 1% significance level, indicating a non-linear "U"-shaped relationship between artificial intelligence and enterprises' green innovation. By replacing the measurement methods of the explanatory variable and the explained variable, the robustness of the conclusion of Hypothesis H1 is further demonstrated.

4.2.3. Instrumental variables

The previous conclusions may have the endogeneity problem caused by reverse causality. On the one hand, the development of artificial intelligence technology can promote enterprises' green innovation; on the other hand, enterprises with a high level of green innovation may have a relatively high level of artificial intelligence technology. Therefore, in order to reduce the interference of potential reverse causality on the research conclusions, this paper adopts the instrumental variable method for testing to ensure the accuracy and reliability of the research results.

This paper employs two different instrumental variables. Firstly, the artificial intelligence and its squared term in the first lag period are used as instrumental variables, and the main reasons are as follows: On the one hand, the artificial intelligence in the first lag period is highly correlated with the level of artificial intelligence technology of enterprises; on the other hand, the artificial intelligence in the first lag period is unlikely to have an impact on the green innovation of the sample enterprises. Therefore, it meets the requirements of both correlation and exogeneity simultaneously. Secondly, the industry annual averages of the artificial intelligence and its squared term of other enterprises in the same industry and the same year are selected as instrumental variables. The reasons are as follows: Firstly, there is a strong internal correlation between the annual industry average of artificial intelligence of other enterprises and the artificial intelligence of an enterprise; Secondly, the annual industry average of artificial intelligence of other enterprises is less likely to be directly affected by the green innovation activities of a certain enterprise.

Table 5 reports the regression results of the first stage and the second stage of the instrumental

variable method. Columns (3) to (5) show the regression results with the artificial intelligence in the first lag period as the instrumental variable. Columns (3) and (4) indicate that the artificial intelligence and its squared term are highly correlated with the instrumental variable. The result of the Kleibergen-Paap rk LM statistic in the regression result of the second stage is significant at the 1% significance level, successfully passing the under-identification test of the instrumental variable, which further verifies the validity of the model specification. At the same time, according to the Kleibergen-Paap rk F statistic, this value exceeds the critical value of the weak instrumental variable test set by Stock-Yogo at the 10% significance level, thus proving that the instrumental variable is not a weak instrumental variable. Column (5) reports the results of the second-stage regression of the instrumental variable. The coefficient of the first-degree term of artificial intelligence is significantly negative at the 1% level, and the coefficient of its squared term is significantly positive at the 1% level, once again verifying that artificial intelligence has a "U"-shaped impact on enterprises' green innovation. Columns (6) to (8) show the regression results with the average value of artificial intelligence of other enterprises in the same industry in the same year as the instrumental variable. The regression results are still consistent with the benchmark regression results. After excluding the interference of endogeneity, the conclusion that artificial intelligence has a "U"-shaped impact on enterprises' green innovation, which first inhibits and then promotes, still holds, further proving the robustness of the conclusions of this paper.

Table 5 Robustness test.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Replacement of explanatory variable	Replacement of explained variable	Phase I		Phase II	Phase I		Phase II
	GI1	Int1	Int	Int ²	GI	Int	Int ²	GI
L.Int			-0.411*** (0.113)	-8.350*** (1.026)				
L.Int ²			0.082*** (0.011)	1.274*** (0.098)				
Int	-0.327*** (0.101)	-0.028** (0.014)			-0.770*** (0.250)			-3.333*** (0.605)
Int ²	0.033*** (0.010)	0.005*** (0.002)			0.070*** (0.023)			0.414*** (0.076)
Int_mean						1.381*** (0.219)	6.822*** (2.148)	
Int_mean ²						-0.112*** (0.022)	-0.426** (0.216)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic					166.716			50.260

Kleibergen- Paap rk Wald F statistic					52.554			21.363
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4.3. Mechanism analysis

According to the previous theoretical analysis, there may be transmission paths of "artificial intelligence - absorptive capacity - green innovation", "artificial intelligence - human capital - green innovation", and "artificial intelligence - financing constraints - green innovation" between artificial intelligence and the development of enterprises' green innovation. With the rapid development of artificial intelligence, the absorptive capacity and the level of human capital of enterprises may first decrease and then increase, showing a "U"-shaped non-linear relationship; while the financing constraints of enterprises may first increase and then decrease, showing an inverted "U"-shaped non-linear relationship. Therefore, Equation (2) is constructed to verify the establishment of Hypotheses H2 and H3. According to the setting of Model (2), Mediator represents the mediating variable, which is represented by three variables: absorptive capacity (Abso), human capital (Human), and financing constraints (SA), and the coefficients of β_1 and β_2 are mainly concerned.

$$Mediator_{it} = \beta_0 + \beta_1 Int_{it} + \beta_2 Int^2_{it} + \sum \beta_k controls_{it} + firm + year + \varepsilon_{it} \quad (2)$$

4.3.1. Analysis of Absorptive Capacity Mechanisms

Absorptive Capacity (Abso). Drawing on the research of Tsai (2009), the intensity of a firm's R&D investment is used to measure its absorptive capacity. The greater the intensity of a firm's R&D investment, the stronger its ability to absorb new technologies. The specific measurement method is: Abso = the amount of a firm's R&D investment / operating revenue. Column (1) of Table 6 shows that the coefficient of the first-degree term of artificial intelligence is significantly negative, and the coefficient of the second-degree term is significantly positive, indicating that the impact of artificial intelligence on the absorptive capacity of enterprises presents a "U"-shaped relationship. That is, with the development of artificial intelligence, the ability of enterprises to absorb new technologies first decreases and then increases. In the initial stage of the development of artificial intelligence technology, the ability of enterprises to absorb new technologies does not match the development speed of new technologies, and the green innovation ability of enterprises will be restricted. When artificial intelligence develops to a certain stage, the ability of enterprises to adapt to and absorb new technologies is enhanced, which can effectively promote the green innovation ability of enterprises. Therefore, artificial intelligence affects the absorptive capacity of enterprises, and then has a "U"-shaped impact on green innovation, verifying Hypothesis H2.

4.3.2. Analysis of human capital mechanism

Human Capital (Human). The ratio of R&D personnel to the total number of employees is used to measure the level of human capital in enterprises. Column (2) of Table 6 shows that the coefficient of the first - degree term of artificial intelligence is significantly negative and the coefficient of the second - degree term is significantly positive, indicating that the impact of artificial intelligence on the human capital of enterprises presents a "U" - shaped relationship of first inhibition and then promotion. In the initial stage of the development of artificial intelligence technology, the substitution effect on the enterprise labor force structure is greater than the creation effect, and the level of human capital in enterprises first decreases, and the green innovation ability of enterprises decreases accordingly. When the development of artificial intelligence technology exceeds the critical value, artificial intelligence creates more jobs and attracts more highly - skilled talents, and

the creation effect on the labor force structure gradually becomes greater than the substitution effect. The level of human capital in enterprises rises, and the green innovation ability of enterprises rises accordingly. Therefore, artificial intelligence affects the level of human capital in enterprises, and then has a "U" - shaped impact on green innovation, verifying Hypothesis H3.

Table 6 Mechanism analysis

Variable	(1)	(2)
	Abso	Human
Int	-0.009* (0.005)	-0.159*** (0.013)
Int^2	0.001** (0.000)	0.016*** (0.001)
Constant	0.040** (0.018)	0.559*** (0.043)
Controls	Yes	Yes
Year	Yes	Yes
Company	Yes	Yes
N	21018	20210
R2	0.819	0.817

4.4. Heterogeneity analysis

4.4.1. Size heterogeneity

This paper divides the research sample into two groups based on the median of enterprise size: large - scale enterprises (size = 1) and small - scale enterprises (size = 0), and conducts grouped regression. As shown in the regression results of columns (1) and (2) of Table 7, artificial intelligence in small - scale enterprises has a "U" - shaped impact on green innovation, first inhibiting and then promoting. The possible reason is that small - scale enterprises have certain limitations in risk - taking and resource allocation compared with large - scale enterprises, which leads them to be more cautious in the initial investment and application of artificial intelligence technology. Small - scale enterprises may need a longer time to accumulate sufficient resources and capabilities to achieve the transformation from the inhibitory effect of artificial intelligence technology investment on green innovation to the promoting effect.

4.4.2. Equity Heterogeneity

This paper divides the entire sample into two types according to the nature of enterprise ownership: state-owned enterprises (soe = 1) and non-state-owned enterprises (soe = 0), and conducts grouped regression. Columns (3) and (4) show the regression results of different enterprise natures. In non-state-owned enterprises, the impact of artificial intelligence on enterprises' green innovation presents a "U"-shaped relationship, while in state-owned enterprises, such an impact does not occur. The possible reason is that non-state-owned enterprises can quickly respond to changes in market demand. During the adaptation period, enterprises need to adjust and optimize artificial intelligence technology. This process may involve the reallocation of resources, the optimization of work processes, and the upgrading of employees' skills. These factors may have an inhibitory effect on green innovation activities in the short term. As enterprises gradually overcome these challenges, the positive effects of artificial intelligence technology gradually emerge, thus promoting the development of green innovation.

4.4.3. Heterogeneity of the degree of competition in the industry

The Herfindahl Index is used to measure the degree of industry competition. In this paper, the research sample is divided into two groups according to the median of the degree of competition: enterprises with a high degree of competition ($hhi = 1$) and enterprises with a low degree of competition ($hhi = 0$). The regression results are shown in columns (5) and (6). Only in enterprises with a low degree of competition does the impact of artificial intelligence on green innovation present a "U" shape. The possible reason is that enterprises with a low degree of competition lack urgent market competition pressure in the short term and may be more willing to take the risks of technological innovation. In the initial stage, due to the immaturity of the technology, it may have an inhibitory effect on green innovation. However, in the long run, such bold attempts at new technologies and continuous investment can accumulate valuable experience for enterprises, thus promoting the process of green innovation.

4.4.4. High-tech industry heterogeneity

According to the Classification of High-tech Industries (Manufacturing) (2017), the sample enterprises are divided into non-high-tech industries ($hightech = 0$) and high-tech industries ($hightech = 1$), and regression analyses are conducted respectively. The results are shown in columns (7) and (8). For high-tech enterprises, the coefficient of the first-degree term of artificial intelligence is significantly negative, and the coefficient of the second-degree term is significantly positive, while the regression coefficients of non-high-tech enterprises are not significant. This indicates that the impact of artificial intelligence in high-tech enterprises on green innovation presents a non-linear relationship of first inhibition and then promotion. The possible reason is that high-tech enterprises usually have strong capabilities of technological absorption and transformation, and they can integrate artificial intelligence technology into the green innovation process more quickly. In the initial stage, due to the challenges in the process of technological integration and adaptation, the effect of green innovation may be inhibited. However, with the in-depth application and optimization of the technology, it will eventually promote the development of green innovation.

Table 7 Heterogeneity analysis

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large	Small	National	Private	high competition	low competition	non-high-tech	high-tech
Int	-0.141 (0.134)	-0.419*** (0.132)	0.069 (0.165)	-0.384*** (0.104)	-0.082 (0.124)	-0.418*** (0.130)	-0.034 (0.112)	-0.579*** (0.148)
Int ²	0.010 (0.014)	0.045*** (0.014)	-0.009 (0.017)	0.036*** (0.011)	0.005 (0.013)	0.039*** (0.013)	-0.000 (0.012)	0.057*** (0.015)
Constant	1.776*** (0.504)	0.733 (0.452)	0.056 (0.702)	1.238*** (0.380)	0.560 (0.473)	1.278*** (0.493)	0.777* (0.455)	1.310** (0.514)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10513	10505	5327	15691	10528	10490	10989	10029
R2	0.692	0.589	0.701	0.636	0.698	0.606	0.657	0.658

5. Discussion

Artificial intelligence has a non-linear impact on enterprises' green innovation. Will this result be affected by other external conditions? This paper intends to analyze the impact of artificial intelligence on enterprises' green innovation from the perspective of media attention.

Media attention can provide a broader platform for showcasing artificial intelligence (AI) technologies and increase public awareness opportunities. Through media coverage, the latest advancements and application cases of AI can be rapidly disseminated to the public, enhancing their understanding and recognition of AI technologies. This widespread information dissemination facilitates the further development and application of AI. Simultaneously, it promotes the integration of AI technologies across industries, highlighting their potential in diverse fields and accelerating the formation of digital and intelligent innovations. Such reporting not only stimulates innovation within industries but also attracts more investment and talent, conveying new technologies and products to the public and accelerating AI advancement.

Based on media reporting tendencies, coverage can be categorized into positive, negative, and neutral types. To attract attention and spark public discussion, media often prioritize reporting negative events that draw governmental and public concern. Fu (2023) found that compared to positive coverage, negative media reporting exerts a more significant incentive effect on corporate environmental investments. Media scrutiny can influence corporate environmental pollution behaviors, prompting companies to intensify efforts in environmental management and technological innovation, thereby fostering green innovation (Wang et al., 2022). Public access to environmental information about enterprises through news media helps alleviate information asymmetry between the public and businesses, enabling investors to make wiser decisions and motivating companies to adopt green innovation initiatives (Geng et al., 2023).

Based on the above analysis, this paper adds adjustment variables on the basis of model (1) and constructs the following adjustment effect model:

$$GI_{it} = \delta_0 + \delta_1 Int_{it} + \delta_2 Int^2_{it} + \delta_3 media_{it} + \delta_4 media_{it} * Int_{it} + \delta_5 media_{it} * Int^2_{it} + \sum \delta_k controls_{it} + firm + year + \varepsilon_{it} \quad (3)$$

Drawing on the research of Aerts & Cormier (2009), this paper selects the media report data provided by the CNRDS financial database, including the number of positive reports (e) and the number of negative reports (c). The Janis-Fadner coefficient (J-F) is used to construct the media attention (media) indicator. The specific calculation formula is as follows: t is the sum of the number of positive reports and the number of negative reports. When the number of positive reports obtained by an enterprise increases, media approaches 1, indicating that the enterprise is under less media supervision pressure; if the number of negative reports of the enterprise increases, media approaches -1, meaning that the enterprise is under greater media supervision pressure. That is, the larger the coefficient of media, the smaller the media pressure.

$$media = \begin{cases} \frac{e^2 - ec}{t^2}, & e > c \\ \frac{ec - c^2}{t^2}, & e < c \\ 0, & e = c \end{cases}$$

The moderating effect of media attention (media) is shown in the results of column (1) of Table 8. The coefficient of the interaction term between the quadratic term of artificial intelligence and media attention is significantly positive at the 10% significance level, indicating that the increase in media attention has improved the "U"-shaped relationship between artificial intelligence and

enterprises' green innovation. On the one hand, since $(\delta_1\delta_5 - \delta_2\delta_4 < 0)$, with the increase of media attention, the inflection point of the "U"-shaped relationship between artificial intelligence and enterprises' green innovation shifts to the left, indicating that the process of artificial intelligence promoting green innovation arrives more quickly. On the other hand, the coefficient of the interaction term between media attention and the quadratic term of artificial intelligence is significantly positive and has the same sign as the coefficient of the quadratic term of artificial intelligence. This indicates that with the increase of media attention, the non-linear impact curve of artificial intelligence on enterprises' green innovation becomes steeper. Specifically, before the inflection point, the inhibitory effect of artificial intelligence on enterprises' green innovation becomes more significant; after the inflection point, the promoting effect of artificial intelligence on enterprises' green innovation is correspondingly enhanced. The moderating effect is shown in Figure 4. For enterprises with high media attention, the "U"-shaped relationship between the development level of artificial intelligence and enterprises' green innovation is more obvious. In contrast, for enterprises with low media attention, the inflection point value of the "U"-shaped relationship is larger, indicating that the inhibitory effect of artificial intelligence on enterprises' green innovation lasts longer. This shows that for enterprises with high media attention, the impact of artificial intelligence on green innovation is more significant. The reason is that the increased external attention to the enterprise makes the enterprise pay more attention to artificial intelligence technology, thus increasing the investment intensity, promoting the integration of technology and innovation, and accelerating the application and diffusion of artificial intelligence technology in green innovation. In addition, the attention of external media can enhance the public image and social responsibility awareness of the enterprise, and encourage the enterprise to take more active measures in green innovation. This external pressure and incentive mechanism make the enterprise more proactive and rapid in using artificial intelligence technology to promote the level of green innovation.

Table 8 Analysis of moderating effect.

Variable	(1)
	Media
Int	-0.248*** (0.090)
Int ²	0.023*** (0.009)
sub	
Int*sub	
Int ² *sub	
media	0.007 (0.015)
Int*media	-0.416* (0.234)
Int ² *media	0.046** (0.023)
Constant	0.961*** (0.335)

Controls	是
Year	是
Company	是
N	21018
R2	0.654

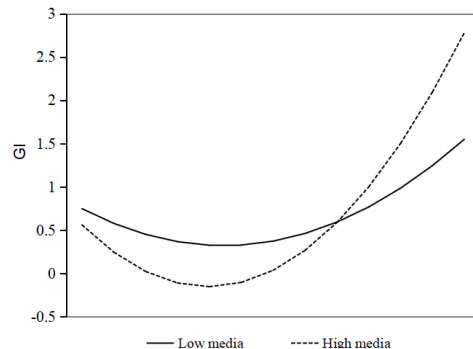


Figure 3 Diagram of the moderating effect of media attention

6. Conclusions

6.1. Main Conclusions

Based on the data of listed manufacturing enterprises in Shanghai and Shenzhen A-share markets from 2010 to 2023, this paper conducts theoretical and empirical analyses on the relationship between artificial intelligence and green innovation, and mainly draws the following conclusions: (1) The impact of artificial intelligence on enterprises' green innovation presents a non-linear "U"-shaped relationship, and this conclusion still holds after a series of robustness tests. (2) In terms of the mechanism of action, from the two perspectives of absorptive capacity and human capital, the "U"-shaped relationship between them is analyzed. (3) The heterogeneity analysis reveals that in small-scale enterprises, non-state-owned enterprises, enterprises with a low degree of competition, and high-tech enterprises, the impact of artificial intelligence on enterprises' green innovation, which first inhibits and then promotes, is more obvious. (4) Further analysis shows that media attention can positively moderate the "U"-shaped relationship between artificial intelligence and enterprises' green innovation.

6.2 Policy recommendations

Firstly, enterprises should seize the development opportunities of artificial intelligence and use intelligent technologies to promote green innovation, recognizing that artificial intelligence technology has a two-edged sword effect on green innovation. In the initial stage, due to uncertainties such as technology integration, long investment payback periods, and high risks, artificial intelligence may have a certain inhibitory effect on green innovation. The government should introduce a series of supportive measures, such as providing R & D subsidies and tax incentives, to reduce the R & D costs and technological risks of enterprises and encourage them to actively explore the deep integration of artificial intelligence and green technologies. As artificial intelligence technology continues to mature and green innovation practices deepen, the government should adjust its policies in a timely manner, strengthen the protection and promotion of green innovation achievements, and promote the in-depth integration and development of artificial intelligence and the green industry.

Secondly, encourage enterprises to cooperate with universities and research institutions to

promote technology transfer and knowledge sharing between enterprises and research institutions, and support enterprises to enhance employees' absorptive capacity for artificial intelligence technology through training. Support enterprises in introducing and cultivating high-end talents to strengthen their R & D capabilities in the field of artificial intelligence, and improve the skill level of the labor force, especially skills related to artificial intelligence, through training. The government can set up special funds or provide low-interest loans to help enterprises, especially small-scale and non-state-owned enterprises, solve financing problems. At the same time, promulgate some policies to encourage financial institutions to provide more financial support for green innovation projects. It can increase government subsidies for green innovation projects to encourage enterprises to carry out green innovation. Through media publicity and public education, raise public awareness of the importance of green innovation and increase social attention and support for green innovation projects.

Thirdly, provide more opportunities for small-scale and non-state-owned enterprises to help them make breakthroughs in artificial intelligence and green innovation. Through policy guidance, encourage large enterprises to cooperate with small-scale enterprises. At the same time, the government can introduce policies to ensure good market competition, encourage enterprises to improve product quality and production efficiency through innovation to adapt to market competition. Provide policy preferences for high-tech enterprises, including tax exemptions and financial support, to promote their development in artificial intelligence and green innovation.

References

- [1] Feng Z, Chen W. Environmental regulation, green innovation, and industrial green development: An empirical analysis based on the Spatial Durbin model[J]. *Sustainability*, 2018, 10(1): 223.
- [2] Liao Y, Qiu X, Wu A, et al. Assessing the impact of green innovation on corporate sustainable development[J]. *Frontiers in Energy Research*, 2022, 9: 800848.
- [3] Amore M D, Bennedsen M. Corporate governance and green innovation[J]. *Journal of Environmental Economics and Management*, 2016, 75: 54-72.
- [4] Zhu Z, Tan Y. Can green industrial policy promote green innovation in heavily polluting enterprises? Evidence from China[J]. *Economic Analysis and Policy*, 2022, 74: 59-75.
- [5] Lian G, Xu A, Zhu Y. Substantive green innovation or symbolic green innovation? The impact of ER on enterprise green innovation based on the dual moderating effects[J]. *Journal of Innovation & Knowledge*, 2022, 7(3): 100203.
- [6] Aghion P, Jones B F, Jones C I. Artificial intelligence and economic growth[M]. Cambridge, MA: National Bureau of Economic Research, 2017.
- [7] Hussain M, Yang S, Maqsood U S, et al. Tap** into the green potential: The power of artificial intelligence adoption in corporate green innovation drive[J]. *Business Strategy and the Environment*, 2024.

- [8] Lee C C, Qin S, Li Y. Does industrial robot application promote green technology innovation in the manufacturing industry?[J]. *Technological Forecasting and Social Change*, 2022, 183: 121893.
- [9] Gan J, Liu L, Qiao G, et al. The role of robot adoption in green innovation: Evidence from China[J]. *Economic Modelling*, 2023, 119: 106128.
- [10] Liang P, Sun X, Qi L. Does artificial intelligence technology enhance green transformation of enterprises: Based on green innovation perspective[J]. *Environment, Development and Sustainability*, 2024, 26(8): 21651-21687.
- [11] Wang Q, Sun T, Li R. Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects[J]. *Energy & Environment*, 2023: 0958305X231220520.
- [12] Feng F, Li J, Zhang F, et al. The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability[J]. *International Review of Economics & Finance*, 2024, 96: 103649.
- [13] Patrick G, Patrick H. Digital sustainable entrepreneurship: A business model perspective on embedding digital technologies for social and environmental value creation[J]. *Journal of Cleaner Production*, 2020, 272:122817.
- [14] Zhao P, Gao Y, Sun X. How does artificial intelligence affect green economic growth?—Evidence from China[J]. *Science of The Total Environment*, 2022, 834: 155306.
- [15] Brynjolfsson E. The Turing Trap: The Promise & Peril of Human-Like Artificial Intelligence[J]. *Papers*, 2022.
- [16] Yin S, Yu Y. An adoption-implementation framework of digital green knowledge to improve the performance of digital green innovation practices for industry 5.0[J]. *Journal of Cleaner Production*, 2022, 363: 132608.
- [17] Petroni G, Bigliardi B, Galati F. Rethinking the Porter hypothesis: The underappreciated importance of value appropriation and pollution intensity[J]. *Review of policy Research*, 2019, 36(1): 121-140.
- [18] Zhong K, Song L. Artificial intelligence adoption and corporate green innovation capability[J]. *Finance Research Letters*, 2025, 72: 106480.
- [19] Liang P, Sun X, Qi L. Does artificial intelligence technology enhance green transformation of enterprises: Based on green innovation perspective[J]. *Environment, Development and Sustainability*, 2024, 26(8): 21651-21687.
- [20] Aghion P, Bechtold S, Cassar L, et al. The causal effects of competition on innovation: Experimental evidence[J]. *The Journal of Law, Economics, and Organization*, 2018, 34(2): 162-195.
- [21] Dixon J, Hong B, Wu L. The robot revolution: Managerial and employment consequences for firms[J]. *Management Science*, 2021, 67(9): 5586-5605
- [22] Rajagopal N K, Qureshi N I, Durga S, et al. Future of business culture: An artificial intelligence - driven digital framework for organization decision - making process[J]. *Complexity*, 2022, 2022(1): 7796507.
- [23] Su H, Qu X, Tian S, et al. Artificial intelligence empowerment: The impact of research and development investment on green radical innovation in high - tech enterprises[J]. *Systems Research and Behavioral Science*, 2022, 39(3): 489-502.
- [24] Cohen W M, Levinthal A. A new perspective on learning and innovation[J]. *Administrative science Quarterly*, 1990, 35: 128r152.
- [25] Brynjolfsson E, Rock D, Syverson C. Artificial intelligence and the modern productivity paradox[J]. *The economics of artificial intelligence: An agenda*, 2019, 23(2019): 23-57.
- [26] Joseph S, Kolade T M, Obioha Val O, et al. AI-powered information governance: Balancing automation and human oversight for optimal organization productivity[J]. *Asian Journal of Research in Computer Science*, 2024, 17(10): 10.9734.

- [27] Gao Y, Liu S, Yang L. Artificial intelligence and innovation capability: A dynamic capabilities perspective[J]. *International Review of Economics & Finance*, 2025: 103923.
- [28] Jarrahi M H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making[J]. *Business horizons*, 2018, 61(4): 577-586.
- [29] Wu K, Liu S, Zhu M, et al. The impact of digital transformation on resource mismatch of Chinese listed companies[J]. *Scientific Reports*, 2024, 14(1): 9011.
- [30] Aboelmaged M, Hashem G. Absorptive capacity and green innovation adoption in SMEs: The mediating effects of sustainable organisational capabilities[J]. *Journal of cleaner production*, 2019, 220: 853-863.
- [31] Albort-Morant G, Leal-Rodríguez A L, De Marchi V. Absorptive capacity and relationship learning mechanisms as complementary drivers of green innovation performance[J]. *Journal of knowledge management*, 2018, 22(2): 432-452.
- [32] Ramos M E, Garza-Rodríguez J, Gibaja-Romero D E. Automation of employment in the presence of industry 4.0: The case of Mexico[J]. *Technology in Society*, 2022, 68: 101837.
- [33] Jetha A, Bonaccio S, Shamaee A, et al. Divided in a digital economy: Understanding disability employment inequities stemming from the application of advanced workplace technologies[J]. *SSM-Qualitative Research in Health*, 2023, 3: 100293.
- [34] Autor D, Salomons A. Is automation labor-displacing? Productivity growth, employment, and the labor share[R]. *National Bureau of Economic Research*, 2018.
- [35] Shen Y, Zhang X. The impact of artificial intelligence on employment: the role of virtual agglomeration. *Humanities and Social Sciences Communications*, 11 (1), 1–14[EB/OL].(2024)
- [36] Chen Z. Ethics and discrimination in artificial intelligence-enabled recruitment practices[J]. *Humanities and Social Sciences Communications*, 2023, 10(1): 1-12.
- [37] Polak P. Welcome to the digital era—the impact of AI on business and society[J]. *Society*, 2021, 58(3): 177-178.
- [38] Johnson M, Jain R, Brennan-Tonetta P, et al. Impact of big data and artificial intelligence on industry: developing a workforce roadmap for a data driven economy[J]. *Global Journal of Flexible Systems Management*, 2021, 22(3): 197-217.
- [39] Wang S, Wang Y, Li C. AI-driven capital-skill complementarity: Implications for skill premiums and labor mobility[J]. *Finance Research Letters*, 2024, 68: 106044.
- [40] Morandini S, Fraboni F, De Angelis M, et al. The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations[J]. *Informing Science*, 2023, 26: 39-68.
- [41] Singh S K, Del Giudice M, Chierici R, et al. Green innovation and environmental performance: The role of green transformational leadership and green human resource management[J]. *Technological forecasting and social change*, 2020, 150: 119762.
- [42] Song Y, Zhang Y, Zhang Z, et al. Artificial intelligence, digital finance, and green innovation[J]. *Global Finance Journal*, 2025, 64: 101072.
- [43] Zhong K, Song L. Artificial intelligence adoption and corporate green innovation capability[J]. *Finance Research Letters*, 2025, 72: 106480.
- [44] Liu X, Cifuentes-Faura J, Yang X, et al. The green innovation effect of industrial robot applications: Evidence from Chinese manufacturing companies[J]. *Technological Forecasting and Social Change*, 2025, 210: 123904.

- [45] Haans R F J , Pieters C , He Z L .Thinking about U: Theorizing and testing U - and inverted U - shaped relationships in strategy research[J].Strategic Management Journal, 2016, 37(7):1177-1195.
- [46] Quan X, Ke Y, Qian Y, et al. CEO foreign experience and green innovation: Evidence from China[J]. Journal of Business Ethics, 2021: 1-23.
- [47] Tsai K H. Collaborative networks and product innovation performance: Toward a contingency perspective[J]. Research policy, 2009, 38(5): 765-778.
- [48] Fu L. Why bad news can be good news: The signaling feedback effect of negative media coverage of corporate irresponsibility[J]. Organization & Environment, 2023, 36(1): 98-125.
- [49] Wang F, Sun Z, Feng H. Can media attention promote green innovation of Chinese enterprises? Regulatory effect of environmental regulation and green finance[J]. Sustainability, 2022, 14(17): 11091.
- [50] Geng Y, Chen J, Liu T, et al. Public environmental attention, media coverage, and corporate green innovation: evidence from heavily polluting industries in China[J]. Environmental Science and Pollution Research, 2023, 30(37): 86911-86926.
- [51] Aerts W, Cormier D. Media legitimacy and corporate environmental communication[J]. Accounting, organizations and society, 2009, 34(1): 1-27.