How Artificial Intelligence Empowers Corporate Green Innovation: Mechanism and Evidence from China's Manufacturing Industry

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Abstract—Corporate Green Innovation (CGI) is essential for coping with environmental challenges and promoting economic growth. To explore whether and how the application of Artificial Intelligence (AI) can promote CGI, and which types of enterprises can benefit more from AI in enhancing CGI, this paper takes the establishment of China's National New Generation AI Innovation and Development Pilot Zone (NAIPZ) as a quasi-natural experiment to examine the impact of AI on CGI. The results confirm that AI significantly promotes CGI, especially in the eastern region, non-SOEs, and industries with higher competition or lower financing constraints. Mechanism analysis emphasizes that corporate productivity and Internal Governance (IG) are key channels. Based on the research results, we suggest that promote the further development of CGI by reducing corporate productivity, formulating and implementing policy differently, helping disadvantaged enterprise to unite high competition and low-financing-constrained enterprises together. The research results provide a transferable implementation approach for governments and enterprise to promote CGI with AI.

Keywords—difference-in-differences method, double machine learning model, artificial intelligence, corporate green innovation, corporate productivity, internal governance

I. INTRODUCTION

In the current global situation, the growth trends of each country's GDP are not optimistic, and innovation has become a powerful means to drive economic growth (Department of Economic Social Affairs, 2024; Fagerberg & Srholec, 2008). Meanwhile, the issues of environmental pollution and climate change across the globe are becoming increasingly severe. Green technologies provide crucial technological support for the achievement of sustainable development goals (Guo & Xu, 2024). Therefore, promoting CGI is becoming an important choice under the pressure of economy and environment. CGI refers to innovations in green products or processes, such as technological advancements in waste recycling, energy conservation and emissions reduction. The development and application of green technologies serve to harmonize economic and environmental goals by minimizing ecological footprints (Omri, 2020). Therefore, the question of how to promote CGI has emerged as a key focus in the academic literature. Based on the policy background and research background, we propose two research questions: Can AI enhance corporate green innovation capabilities? Can AI promote CGI by improving corporate productivity? Can AI significantly promote CGI by optimizing IG?

In 2017, the strategic plan for building an AI innovation pilot zone in the new era was proposed. In 2019, acting on the principle of "first try, first implement," the Chinese government issued the "NAIPZ Construction Guidance". This policy officially marked the beginning of a new stage for AI development in China. The specific content is displayed in Table 1. The policy goal is to enhance AI technology innovation ability, promote the construction of smart economy and smart society, and aim to cope with future risks and promote people-oriented sustainable intelligent development.

Table 1. Classification of AI innovation pilot zones by year and pilot region

Year	Designated Cities
2019	Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, Deqing
2020	Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, Wuhan
2021	Suzhou, Changsha, Zhengzhou, Shenyang, Harbin

We employ the NAIPZ establishment as a quasi-natural experiment. The analysis uses data from China's A-share listed manufacturing sector between 2013 and 2023, using the multi-period DID and the Double Machine Learning model (DML) to systematically evaluate the impact of AI on CGI. The results show that AI has a significant role in promoting CGI, and AI can significantly promote CGI by optimizing the IG and improving the corporate productivity.

II. LITERATURE REVIEW

Recent research demonstrates, corporate governance (Albloushi *et al*., 2023), public procurement (Cheng *et al*., 2023), investor attention and network media (Liu *et al*., 2024), distorted land prices (Xiao *et al*., 2024), educational background of female executives (Xie & Li, 2025) and green subsidies (An *et al*., 2025) have an impact on CGI. In addition, empirical studies by Geng *et al*. (2023) and Han and Mao (2024) have shown that digitization significantly affects CGI, and many scholars have further enriched this research field. Zhao and Wang (2025)'s empirical research shows that AI, as an important driver of the digitization process, has a positive impact on promoting CGI. AI is rewiring our economy and society, unlocking new solutions for CGI. The integration of CGI and AI is becoming a key driving force to address global environmental challenges and enhance the quality of economic growth.

Our review indicates that the literature exploring

the mechanisms linking AI to CGI has been narrow., mainly focusing on corporate governance, such as boosting human capital accumulation, optimizing organizational management efficiency (Dong *et al*., 2025), strengthening internal control (Jiang *et al*., 2024), and optimizing internal governance (Zhao & Wang, 2025).

At the same time, reducing financing constraints (Zhong & Song, 2025) and increasing R & D investment (Lin & Zhu, 2025) as new intermediary mechanisms have been incorporated into the analytical framework of AI and CGI by scholars. However, increasing R & D investment is not easy for corporates. corporates need to optimize the allocation of human, material and financial resources for green innovation activities. Therefore, improving corporate productivity may be an important way to optimize resource allocation and increase investment in CGI.

III. HYPOTHESIS DEVELOPMENT

A. AI and CGI

CGI refers to the development and implementation of new technologies and processes to promote environmental sustainability. It is indispensable for the sustained development of corporations, the sound functioning of economies, and the stability of global ecosystems (Asni & Agustia, 2022), and become a powerful strategy for advancing high-quality growth, combating climate change, and realizing sustainable development goals. Resource-Based View (RBV) theory holds that the valuable resources owned by enterprises can be transformed into competitive advantages and improve performance through effective organizational mechanisms (Ghasemaghaei, 2021). In the context of sustainable development, corporate urgently need to develop more innovative, higher-tech and more market-potential green technologies to promote green technology progress, build sustainable competitive advantages (Zhang *et al*., 2024). AI is showing great application potential and strategic value in the process of promoting CGI (Zhao & Wang, 2025). A well-established finding in the literature is that AI serves as a significant driver of CGI (Shang *et al*., 2024; Zhao & Wang, 2025; Zhao & Wang, 2024). Based on the relevant theoretical basis and existing research. Accordingly, we posit that:

H1: AI can significantly promote CGI.

B. The Mediating Role of Corporate Productivity

The RBV theory posits that a firm's competitive advantage is fundamentally rooted in its unique resources and capabilities (Ghasemaghaei, 2021). Productivity improvement means that enterprises make more efficient use of resources, which is itself a manifestation of dynamic capabilities. The additional resources released from this, such as manpower, capital, etc, can be reconfigured into green innovation activities and cultivated into new sources of competitive advantage. In addition, Schumpeter's innovation theory holds that Innovation serves as the primary engine that propels economic growth, and enterprises need sufficient profits or resources to fund uncertain innovation activities (Sweezy, 1943). The improvement of productivity directly increases the profit and internal cash flow of corporate, which provides crucial financial support for CGI and drives forward the

advancement of additional breakthrough innovations in CGI. Through empirical research, researchers point out that the AI can significantly enhance the productivity, thus significantly promoting CGI (Liang *et al*., 2024). Therefore, we advance the following hypothesis:

H2: Improving corporate productivity plays an intermediary role in AI and CGI.

C. The Mediating Role of IG

IG includes the behavior of the board of directors, management compensation, capital structure, company charters and regulations, and internal control systems (Gillan, 2006). A stable and efficient institutional environment is crucial for corporations to sustain green innovation. It relies on sound internal governance, which enhances efficiency in decision-making and implementation while ensuring transparency in oversight (Dong *et al*., 2025).

The application of AI reduces the cost of information disclosure and significantly improves information transparency, thereby systematically enhancing CGI (Zhao & Wang, 2025). Specifically, technologies such as automated auditing and real-time monitoring strengthen continuous oversight of key processes in production, R&D, and management. This enhanced supervision helps mitigate moral hazard and fraudulent activities (Han *et al*., 2023), thereby increasing stakeholder trust. Furthermore, as Effah *et al*., (2023) suggest, the detailed data disclosed enables companies to more accurately identify their deficiencies in energy conservation and environmental protection, which in turn drives innovation. The integration of data analytics and process automation further optimizes resource allocation efficiency, providing essential support for these innovation activities (Papagiannidis *et al*., 2023). In addition, by reshaping the work paradigm and skill needs, AI can effectively reshape the human capital structure and shift its focus to higher value areas, thus releasing great potential. As an important factor of corporate internal governance, human capital is the core element to support corporates to carry out CGI. By translating their advantage in professional talent into resilience against environmental regulations and foresight into market demand, companies are powerfully driving the development of sustainable products and a leap forward in green innovation capability.

Therefore, we advance the following hypothesis:

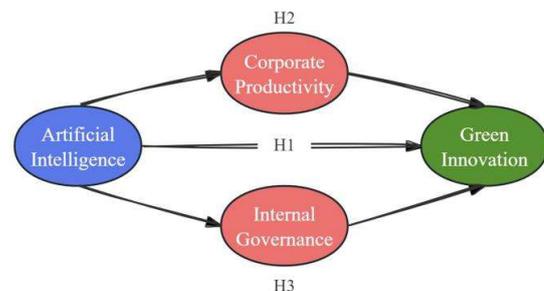H3: AI promotes CGI by optimizing internal governance.

Fig. 1. Theoretical framework.

IV. MODEL AND DATA

A. Model Establishment

The multi-period DID model enable to capture the evolving policy impact. It dynamically assesses how AI

influences CGI by leveraging longitudinal data from before and after the policy implementation. Formulated as follows:

$$CGI_{it}=\beta_0+\beta_1 DID_{it}+\beta_2 Control_{it}+\mu_i+\eta_t+\varepsilon_{it} \quad (1)$$

In this empirical specification, CGI_{it} captures the level of green innovation for firm I in year t. The key explanatory variable DID_{it}, constructed by interacting the NAIPZ policy dummy with a time indicator, serves to quantify the causal impact of AI implementation on CGI. The variable equals 1 if firm i is situated within a pilot zone during year t, and 0 otherwise. Regarding the parameters, β_0 represents the constant term, while β_1—the coefficient of primary interest—estimates the net policy impact using multi-period DID model. β_2 denotes the estimated coefficients of the control variables in the model. In addition, μ_i and λ_t are specified to account for firm and year fixed effects, with ε_{it} denoting the idiosyncratic error term. Then, to uncover the transmission channels through which AI influences CGI, we estimate the following mediation model:

$$Mechanism_{it}=\beta_0+\beta_1 DID_{it}+\beta_2 Control_{it}+\mu_i+\eta_t+\varepsilon_{it} \quad (2)$$

$$CGI_{it}=\beta_0+\beta_1 Mechanism_{it}+\beta_2 Control_{it}+\mu_i+\eta_t+\varepsilon_{it} \quad (3)$$

B. Data and Variable

This study selects Chinese A-share listed manufacturing enterprises from 2013 to 2023 as research samples to examine the effect of AI on CGI. Relevant data come from authoritative databases such as CNRDS, CSMAR, DIB, and Wind. Prior to regression analysis, the sample data undergo the following screening procedures: Exclusion of financial industry enterprises; Removal of firms under special treatment (ST, PT, and *ST) by stock exchanges; Elimination of samples with missing values in key variables; Winsorization of continuous variables at the 1% level to mitigate the influence of extreme values.

This study constructs an enterprise-level policy dummy variable (DID) as a key explanatory variable of the DID by matching the pilot zones with the location of the enterprises. Referring to the practice of Boeing (2016) and Dong *et al.* (2025), we adopt the number of citations of green invention patents as an indicator to measure CGI. The number of citations of green invention patents is added to 1 and processed by natural logarithm.

This paper selects two key factors as the mechanism variables to examine how AI affects CGI: (1) enterprise productivity, including Labor Productivity (LP) and Capital Productivity (CP). (2) enterprise Internal Governance (IG). Referring to the practice of Liang *et al.* (2024), we measure LP by calculating the logarithm of the ratio of business income to the number of employees. Our measure of CP is derived from the natural logarithm of net fixed assets per employee. This study employs the internal control index from the DIB database to measure IG, where a higher index value indicates a higher level of IG.

Refer to the existing literature (Dong *et al.*, 2025; Huang *et al.*, 2024), this paper introduces enterprise scale (Size), asset-liability ratio (Lev), current ratio (Liquid) and cash flow level (Cashflow), revenue growth rate (Growth) and board size (Board) as the control variable into the regression model.

V. ANALYSIS OF EMPIRICAL RESULTS

A. Benchmark Regression Analysis

Table 2 reports the estimates of Eq. (1) on AI's impact on CGI, with model specifications refined sequentially across columns: columns (1) and (2) exclude firm and year fixed effects, while columns (3) and (4) incorporate them; columns (1) and (3) omit control variables, whereas columns (2) and (4) include the full set. The AI coefficient remains significantly positive at the 1% level across all specifications, and its magnitude rises to 0.09 in column 4 (with both fixed effects and controls). These robust results empirically validate H1.

Table 2. The results of the benchmark regression.

VARIABLES	(1)	(2)	(1)	(2)
	CGI	CGI	CGI	CGI
DID	0.121***	0.040**	0.099***	0.090***
	(6.555)	(2.481)	(4.429)	(4.180)
R-squared	0.005	0.018	0.159	0.172
Observations	18,005	17,997	18,005	17,997
id FE	NO	NO	YES	YES
year FE	NO	NO	YES	YES

Note: Robust t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

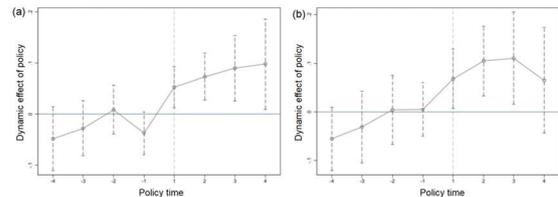*B. Multi-period Parallel Trend Test & Heterogeneity Parallel Trend Test*

Fig. 2. Results of parallel trend test. Note: (a) shows the results of the multi-period parallel trend test and (b) shows the results of the heterogeneity parallel trend test.

The parallel trend assumption, a core prerequisite for DID validity, requires the treatment and control groups to have comparable outcome variable trends pre-policy. To verify this and examine dynamic policy effects, we adopt an event study approach with a heterogeneous-treatment parallel trend test (Sun & Abraham, 2021). The results in Fig. 2 show that pre-policy coefficients are statistically insignificant, while post-policy coefficients turn significantly positive and rise persistently, confirming the parallel trend assumption and the continuously strengthened promotion effect of NAIPZ on CGI, thus validating the reliability of our DID estimates.

C. Placebo Test

This paper conducted 500 random experiments to mitigate the potential bias from unobservable omitted variables in the benchmark regressions (Yang *et al.*, 2021), and the placebo test was carried out by randomly generating treatment groups. As illustrated in Fig. 3, the coefficients derived from this test—using randomly generated pseudo-policy variables—are largely clustered around zero. These values are substantially smaller than the baseline

regression estimate and conform to a normal distribution. In addition, most corresponding p-values fall above conventional significance thresholds, reflecting a general absence of statistical significance. This pattern confirms that the core findings of the study are not attributable to random chance, thereby reinforcing the robustness of the empirical analysis.
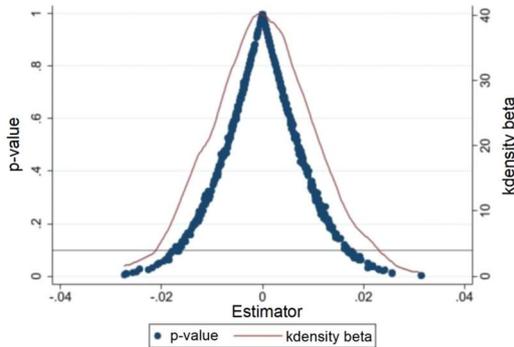

Fig. 3. Placebo test.

D. Dual Machine Learning (DML) Model

CGI is affected by many variables, and these variables may be nonlinear, or there are high-dimensional complex interference factors, so this paper uses DML model for estimation. DML can not only automatically screen out the effective control variable set with high prediction accuracy, but also effectively avoid the threat of model misspecification when dealing with nonlinear data by relying on the advantages of the algorithm, so as to improve the precision and robustness of causal effect assessment. Therefore, this paper sets the sample segmentation ratio to 1: 3, and uses lasso regression, gradient boosting, neural network and random forest algorithm for regression respectively. To further test the sensitivity of the model to the sample segmentation ratio, this paper also resets the sample segmentation ratio to 1: 5, and uses the lasso regression algorithm to estimate again. According to the results of columns (1) to (5) of the Table 3, the benchmark regression results of this paper are still robust.

Table 3. Results from the double machine learning estimator.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	CGI	CGI	CGI	CGI	CGI
DID	0.308***	0.316***	0.323***	0.302***	0.305***
	(15.240)	(16.062)	(14.688)	(15.834)	(15.080)
Constant	−0.001	−0.001	−0.027***	−0.022***	0.001
	(−0.020)	(−0.049)	(−4.473)	(−3.843)	(0.012)
Observations	17,997	17,997	17,997	17,997	17,997
id FE	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

VI. HETEROGENEITY ANALYSIS

A. Regional Heterogeneity

The coefficient of the eastern region shows in Table 4 is 0.096 ($p < 0.01$). This result can be attributed to the favorable conditions in eastern cities, including higher economic complexity and denser industrial clusters, which facilitate the realization of AI's environmental benefits. The coefficients of the central and eastern regions are positive, but the coefficients are low and not significant. This discrepancy may stem from regional variations in economic development levels, degrees of institutional adaptation to the policy, and resource allocation efficiency.

B. Industrial Heterogeneity

To explore the differences in the impact of AI adoption on CGI across corporate ownership types, this study divides the sample into state-owned (SOEs) and non-state-owned (Non-SOEs) enterprises for group regression analysis. The results show that non-state-owned enterprises benefit significantly more from AI adoption in terms of CGI enhancement compared to state-owned enterprises, owing to their more flexible factor allocation (Zhao & Wang, 2025), higher productivity levels, and more market-oriented incentive mechanisms. Additionally, further grouped tests based on industry attributes (regulated & competitive industries) and the degree of financing constraints measured by the SA index (Hadlock & Pierce, 2010) reveal that in competitive industries, AI more significantly promotes CGI by reducing external transaction costs, while firms with lower financing constraints can more effectively leverage AI to improve CGI due to easier access to R&D funding. In conclusion, policy formulation should fully consider differences in firm types and industry characteristics to enhance targeting. Detailed results are presented in Table 4.

Table 4. The results of the heterogeneity test.

VARIABLES	East	Middle	West	SOEs	Non-SOEs	Competitiveness	Regulatory	High	Low
DID	0.096***	0.071	0.049	0.066	0.077***	0.090***	0.049	0.037	0.098***
	(3.806)	(1.248)	(0.706)	(1.224)	(3.195)	(4.057)	(0.636)	(1.078)	(2.970)
Observations	13,112	2,929	1,956	4,098	13,507	15,913	2,084	9,024	8,973
R-squared	0.169	0.176	0.205	0.258	0.148	0.169	0.204	0.178	0.168
id FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

VII. FURTHER ANALYSIS

The findings show that AI promotes CGI mainly through two channels: enhancing enterprise productivity and optimizing IG, with relevant results presented in Table 5. First, AI exerts a significantly positive impact on enterprise productivity at the 1% level, and productivity growth serves as a key driver of CGI, thus validating Hypothesis H2. Second, AI can notably optimize IG, and IG in turn significantly boosts CGI performance, thereby verifying Hypothesis H3. A key finding is that enterprise productivity plays a stronger mediating role than IG in the relationship between AI and CGI, providing actionable guidance for enterprises to advance CGI more efficiently.

Table 5. The results of the mechanism test.

VARIABLES	(1) LP	(2) CGI	(3) CP	(4) CGI	(5) IG	(6) CGI
DID	0.034***	0.097***	6.433***	0.096***	0.006*	0.090***
	(3.118)	(5.747)	(4.144)	(5.680)	−1.736	−4.132
LP		0.050***				
		(3.989)				
CP				0.000***		
				(4.702)		
IG						0.073*
						−1.877
Constant	13.790***	−0.049	1,268.181***	0.109	6.137***	−3.561***
	(4,639.281)	(−0.284)	(3,032.449)	(0.967)	−94.476	(−5.902)
Observations	17,678	17,678	17,675	17,675	17,502	17,502
R-squared	0.814	0.812	0.786	0.812	0.292	0.815
id FE	YES	YES	YES	YES	YES	YES
year FE	YES	YES	YES	YES	YES	YES

Note: Robust t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

VIII. CONCLUSION AND DISCUSSION

A. Conclusion

Based on the panel data of A-share listed manufacturing enterprises from 2013 to 2023, this study takes the NAIPZ as a quasi-natural experiment, and uses multi-period DID and DML methods for systematic evaluation. Benchmark regression and rigorous robustness test show that AI has a significant promoting effect on CGI. Heterogeneity analysis shows that this effect is more prominent in the eastern region, Non-SOEs, competitive industries and the enterprises of low financing constraints. Mechanism analysis shows that AI promotes CGI mainly through two paths: improving productivity and optimizing IG.

B. Recommendations

Based on the findings, the following targeted recommendations are proposed. First, governments should focus on reducing the exploration costs and transformation barriers for AI adoption in CGI by developing industry guidelines, encouraging cluster-based transformation among leading firms, and providing open-source platforms. Enterprises should prioritize high-value AI applications and organizational adaptation to translate efficiency gains into sustained green innovation. Second, regional strategies should be differentiated: leveraging technology clusters in the east to foster interdisciplinary green innovation, while strengthening innovation infrastructure and facilitating technology transfer to the central and western regions. Third, SOEs should accelerate governance reforms—such as adopting market-oriented hiring and dedicated green innovation assessments—and enhance collaboration with universities and non-SOEs to overcome institutional inertia. Lastly, differentiated financial support should be provided: guiding firms with low financing constraints to invest in long-term green R&D, while assisting constrained firms through fast-track green loan approvals and R&D tax incentives. A regional green technology financing platform and a shared case database are recommended to improve resource matching and reduce trial-and-error costs for SMEs.

C. Limitations and Future Prospects

This study has several inherent limitations., which are worthy of further study in the future:

First of all, this paper mainly examines the mediating role of production efficiency and internal governance, which is still limited to the enterprise. However, AI may have an impact on the CGI by influencing external factors. More mechanisms need to be further explored to provide a basis for improving CGI.

Secondly, the design does not encompass an examination of moderating effects. The technical background of corporate executives, media attention and industry competition intensity may significantly regulate the effect of policy implementation. Thirdly, the sample selection of this paper has industry limitations.

This paper focuses on manufacturing enterprises, but service industry, construction industry and other industries may present unique characteristics. It is suggested that the follow-up research should expand the sample coverage, pay special attention to the cross-cutting areas of AI, and refine more universal policy implications through multi-industry comparative research.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Yilin Zhang conducted the theoretical analysis, data collection and analysis, performed the software operation, and wrote the first draft of the manuscript; Ju Jin: was responsible for the conceptualization and methodology design, and provided supervision and guidance throughout the research; Shen Zhong: was responsible for data curation and software supervision, provided overall research oversight, and contributed to the review and editing of the manuscript; all authors have read and approved the final

version of the manuscript.

REFERENCES

Albloushi, B., Alharmoodi, A., Jabeen, F., Mehmood, K., & Farouk, S. 2023. Total quality management practices and corporate sustainable development in manufacturing companies: The mediating role of green innovation. *Management Research Review*, 46(1): 20–45. doi.org/10.1108/MRR-03-2021-0194

An, J., He, G., Ge, S., & Wu, S. 2025. The impact of government green subsidies on corporate green innovation. *Finance Research Letters*, 71, 106378. doi.org/10.1016/j.frl.2024.106378

Asni, N., & Agustia, D. 2022. Does corporate governance induce green innovation? An emerging market evidence. *Corporate Governance: The International Journal of Business in Society*, 22(7): 1375–1389. doi.org/10.1108/cg-10-2021-0389

Boeing, P. 2016. The allocation and effectiveness of China's R&D subsidies-Evidence from listed firms. *Research Policy*, 45(9): 1774–1789. doi.org/10.1016/j.respol.2016.05.007

Cheng, L., Wang, X. H., Zhang, S. P., & Zhao, M. L. 2023. Public procurement, corporate social responsibility and green innovation: Evidence from China. *Environmental Engineering and Management Journal*, 22(12): 2127. doi.org/10.30638/eemj.2023.183

Department of Economic Social Affairs. 2024. *World Economic Situation and Prospects 2024*. United Nations Research Institute for Social Development.

Dong, X., Zhou, N., Zhao, X., & Yang, S. 2025. The impact of artificial intelligence on corporate green innovation: Can" increasing quantity" and" improving quality" go hand in hand? *Journal of Environmental Management*, 376, 124439. doi.org/10.1016/j.jenvman.2025.124439

Effah, N. A. A., Wang, Q., Owusu, G. M. Y., Otchere, O. A. S., & Owusu, B. 2023. Contributions toward sustainable development: a bibliometric analysis of sustainability reporting research. *Environmental Science and Pollution Research*, 30(1): 104–126. doi.org/10.1007/s11356-022-24010-8

Fagerberg, J., & Srholec, M. 2008. National innovation systems, capabilities and economic development. *Research Policy*, 37(9): 1417–1435. doi.org/10.1016/j.respol.2008.06.003

Geng, Y. N., Zheng, Z. Q., & Ma, Y. J. 2023. Digitization, perception of policy uncertainty, and corporate green innovation: A study from China. *Economic Analysis and Policy*, 80: 544–557. doi.org/10.1016/j.eap.2023.09.006

Ghasemaghaei, M. 2021. Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics. *International Journal of Information Management*, 57, 102055. doi.org/10.1016/j.ijinfomgt.2019.102055

Gillan, S. L. 2006. Recent developments in corporate governance: An overview. *Journal of Corporate Finance*, 12(3): 381–402. doi.org/10.1016/j.jcorpfin.2005.11.002

Guo, X., & Xu, J. J. 2024. Can urban digital intelligence transformation promote corporate green innovation? Evidence from China. *Journal of Environmental Management*, 371, 123245, Article 123245. doi.org/10.1016/j.jenvman.2024.123245

Hadlock, C. J., & Pierce, J. R. 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5): 1909–1940.

Han, F., & Mao, X. 2024. Impact of intelligent transformation on the green innovation quality of Chinese enterprises: Evidence from corporate green patent citation data. *Applied Economics*, 56(45): 5342–5359. doi.org/10.1080/00036846.2023.2244256

Han, H. D., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. 2023. Accounting and auditing with blockchain technology and artificial Intelligence: A literature review. *International Journal of Accounting Information Systems*, 48, 100598, Article 100598. doi.org/10.1016/j.accinf.2022.100598

Huang, Y. J., Liu, S. C., Gan, J. W., Liu, B. L., & Wu, Y. X. 2024. How does the construction of new generation of national AI innovative

development pilot zones drive enterprise ESG development? Empirical evidence from China. *Energy Economics*, 140, 108011, Article 108011. doi.org/10.1016/j.eneco.2024.108011

Jiang, L., Xuan, Y., & Zhang, K. 2024. Unlocking innovation potential: the impact of artificial intelligence transformation on enterprise innovation capacity. *European Journal of Innovation Management*, ahead-of-print. doi.org/10.1108/EJIM-07-2024-0809

Liang, P., Sun, X., & Qi, L. 2024. Does artificial intelligence technology enhance green transformation of enterprises: Based on green innovation perspective. *Environment, Development and Sustainability*, 26(8): 21651–21687. doi.org/10.1007/s10668-023-04225-6

Lin, B., & Zhu, Y. 2025. The impact of artificial intelligence policy on green innovation of firms. *Energy Economics*, 148, 108524. doi.org/10.1016/j.eneco.2025.108524

Liu, L. Y., Ge, M., & Ding, Z. R. 2024. Impacts of online media and investor attention on enterprise green innovation. *International Review of Economics & Finance*, 96, 103569, Article 103569. doi.org/10.1016/j.iref.2024.103569

Omri, A. 2020. Technological innovation and sustainable development: does the stage of development matter? *Environmental Impact Assessment Review*, 83, 106398. doi.org/10.1016/j.eiar.2020.106398

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. 2023. Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, 25(1): 123–141. doi.org/10.1007/s10796-022-10251-y

Shang, Y. P., Zhou, S. L., Zhuang, D. L., Zywiolek, J., & Dincer, H. 2024. The impact of artificial intelligence application on enterprise environmental performance: Evidence from microenterprises. *Gondwana Research*, 131: 181–195. doi.org/10.1016/j.gr.2024.02.012

Sun, L., & Abraham, S. 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2): 175–199. doi.org/10.1016/j.jeconom.2020.09.006

Sweezy, P. M. 1943. Professor Schumpeter's theory of innovation. *The Review of Economics and Statistics*, 25(1): 93–96. doi.org/10.2307/1924551

Xiao, Q., Chen, X. H., Gao, J., & Fang, X. B. 2024. Distorted land price and green innovation: empirical evidence from 273 cities in China. *Environment Development and Sustainability*. Retrieved Dec, from <Go to ISI>://WOS:001382784400001

Xie, Q. W., & Li, J. 2025. Educational background of female executives and corporate green innovation. *Finance Research Letters*, 84, 107784, Article 107784. doi.org/10.1016/j.frl.2025.107784

Yang, Q., Gao, D., Song, D., & Li, Y. 2021. Environmental regulation, pollution reduction and green innovation: The case of the Chinese Water Ecological Civilization City Pilot policy. *Economic Systems*, 45(4), 100911. doi.org/10.1016/j.ecosys.2021.100911

Zhang, Z., Luo, X., Du, J., & Xu, B. 2024. Substantive or strategic: Government R&D subsidies and green innovation. *Finance Research Letters*, 67, 105796. doi.org/10.1016/j.frl.2024.105796

Zhao, C., & Wang, L. 2025. Artificial intelligence and enterprise green innovation: Evidence from a quasi-natural experiment in China. *Sustainability*, 17(6), 2455. doi.org/10.3390/su17062455

Zhao, D. Y., & Wang, M. 2024. Smart manufacturing promotes high-quality development of enterprises in China. *Sustainability*, 16(23): 10431, Article 10431. doi.org/10.3390/su162310431

Zhong, K., & Song, L. 2025. Artificial intelligence adoption and corporate green innovation capability. *Finance Research Letters*, 72, 106480. doi.org/10.1016/j.frl.2024.106480