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Corporate Artificial Intelligence and Green Innovation Efficiency: The Roles of Environmental Disclosure, R&D Human Capital and Government Subsidies

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Abstract

Artificial intelligence (AI) is widely promoted as a tool for corporate green transformation, but whether it helps firms convert research and development (R&D) resources into green technologies more efficiently remains unclear. Drawing on the resource-based view and information-asymmetry theory, this study examines whether corporate AI is associated with green innovation efficiency (GEff), whether environmental information disclosure quality (Eidq) transmits this association, and whether government subsidies condition it. Using 28,219 firm-year observations of Chinese A-share listed firms from 2012 to 2024, we measure AI with a text-based index from annual reports and estimate two-way fixed-effects models, complemented by leave-one-out instrumental variables, dynamic specifications, alternative measures including AI patents and bootstrap mediation tests. AI is positively and robustly associated with GEff, an association driven mainly by green invention patents, whereas past GEff does not predict future AI. Eidq and R&D human capital provide significant but modest partial mediating channels, and the AI–GEff association is stronger at higher subsidy levels, particularly for non-innovation subsidies. Formal tests reveal no significant differences across regions, pollution intensity, technology status, life-cycle stages, industries or ownership. The findings suggest that combining AI deployment with credible environmental disclosure and subsidies for AI adoption can support more efficient green innovation.

Keywords: artificial intelligence; green innovation efficiency; environmental information disclosure quality; government subsidies; R&D human capital; resource-based view; Chinese listed firms

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1. Introduction

China's green transformation has accelerated in recent years. In 2024, electricity generated from hydro, nuclear, wind and solar sources reached 3712.6 billion kWh, an increase of 16.4% over the previous year, and the national carbon emissions trading market traded 189 million tons of allowances worth RMB 18.11 billion [1]. For firms, however, how efficiently they transform innovation resources into green technological output matters as much as how much they invest in green technologies. Green innovation efficiency (GEff) captures this input–output relationship. Unlike patent counts, it relates green innovation output to the resources consumed in generating it and therefore offers a more informative basis for evaluating corporate green transformation [2–5]. Improving GEff lowers the cost of green technologies, supports the development of green products and contributes to China's carbon-peaking and carbon-neutrality goals [6–10].

Existing research has identified supply-chain ESG performance, regional digital maturity, market-based environmental regulation and environmental taxes as determinants of GEff [11–14]. Among technological factors, artificial intelligence (AI) has attracted particular attention because it can improve information search, prediction, process control and energy management, thereby restructuring corporate energy use and green R&D [15–21]. Yet AI is double-edged. Its deployment requires digital infrastructure, computing power, electricity, specialized skills and organizational restructuring, which may divert resources from green R&D and increase environmental pressure [22,23]. Whether the enabling effect of AI dominates its crowding-out effect in the efficiency of green innovation is therefore an empirical question.

Three gaps motivate this study. First, most firm-level studies relate AI to the quantity of green innovation output, whereas studies that examine efficiency focus on single industries such as energy or rare earths or on regional AI pilot zones [24–28]. Evidence on whether AI improves the efficiency of green innovation across the population of listed firms, and on which type of green innovation drives this relationship, remains limited. Second, AI may improve the collection, measurement and communication of environmental information [29], but generative AI may also lower the cost of producing persuasive yet selective environmental narratives [30,31]. Whether environmental information disclosure quality (Eidq) is a channel linking AI to GEff, and how large this channel is, has rarely been tested. Third, government subsidies are usually treated as a direct driver of AI or green innovation, even though subsidy allocation is not random [32,33]. Less is known about whether subsidies act as a complementary resource that conditions the translation of AI into green innovation efficiency.

Using 28,219 firm-year observations of Chinese A-share firms listed on the Shanghai and Shenzhen stock exchanges from 2012 to 2024, this study examines the relationship between corporate AI and GEff, the mediating role of Eidq and the moderating role of government subsidies. We find that AI is positively associated with GEff and that this association is concentrated in green invention patents. The association survives high-dimensional fixed effects, leave-one-out instrumental variables that control for industry-level green innovation shocks and dynamic tests showing that past GEff does not predict future AI. Eidq transmits a statistically significant but small portion of the association, and higher government subsidies strengthen it. Formal coefficient-difference tests show that the association does not differ significantly across the subsamples commonly examined in the literature.

This study makes three contributions. First, it distinguishes AI attention disclosed in annual reports from verified AI implementation and green innovation efficiency from green innovation output. By showing that the AI–GEff association is concentrated in green invention patents and that it is robust to alternative AI measures that control for general disclosure verbosity and to a patent-based measure of AI technology, the study provides broad, firm-level evidence on the type of green innovation associated with AI. Second, it integrates the resource-based view with information-asymmetry, signalling and legitimacy theories to explain why Eidq can transmit the effect of AI, identifies R&D human capital as an internal channel through which AI reshapes the innovation workforce, and quantifies these channels using bootstrap confidence intervals and lagged specifications while explicitly distinguishing the completeness of disclosure from the credibility of environmental performance. Third, it treats government subsidies as a boundary condition on the AI–GEff association, addresses subsidy selection with lagged subsidies, high-dimensional fixed effects and a distinction between innovation and non-innovation subsidies, and replaces the common practice of comparing significance levels across subsamples with formal tests [34], thereby correcting claims of heterogeneous effects that are not statistically supported.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data, variables and empirical strategy. Section 4 reports the baseline, identification and robustness results. Section 5 presents the mechanism and heterogeneity analyses. Section 6 discusses the findings, and Section 7 concludes.

2. Literature Review and Hypothesis Development

2.1. Corporate AI and Green Innovation Efficiency

Three concepts need to be distinguished at the outset. AI adoption refers to the actual implementation of AI technologies in production, R&D or management; AI-related disclosure refers to the attention firms devote to AI in public documents; and green innovation output and green innovation efficiency differ in that the former counts green technologies, whereas the latter relates them to the resources used. Prior studies often measure AI through disclosure while interpreting it as adoption, and they often study output while discussing efficiency [35–37]. In this study, AI is measured through disclosure and interpreted as firms' strategic attention to and reported deployment of AI, and the outcome is efficiency.

From the perspective of the resource-based view, firm performance depends on valuable, rare, difficult-to-imitate and well-organized resources [38]. AI can become such a resource when it is combined with complementary data, technical skills, organizational routines and absorptive capacity [39]. Firms that integrate AI into green R&D can improve technological search, simulate and test alternative designs virtually, monitor energy and material flows in real time and reallocate resources toward promising green projects, thereby generating more green technological output per unit of R&D input [18,40]. Empirically, AI has been found to raise the efficiency of technology development in Chinese rare earth enterprises [25], to optimize the production and refining processes of algae-based bioenergy [41], to promote green innovation through direct and spillover effects [42,43] and to improve green innovation efficiency, particularly in firms with stronger dynamic capabilities [28]. Quasi-natural experiments based on China's AI Innovation and Development Pilot Zones reach similar conclusions [26,27].

At the same time, AI imposes infrastructure, learning and integration costs and may increase energy consumption [22,23]. Firms lacking complementary resources may therefore find that these costs offset the potential benefits. Because listed firms in China operate in a policy environment that combines digital-transformation support with the dual-carbon agenda and generally have better access to digital infrastructure and finance, we expect the enabling effect to dominate on average, in line with the view that well-designed environmental pressures and resources can generate innovation offsets [44]. We therefore propose the following:

H1. *Corporate AI is positively associated with green innovation efficiency.*

2.2. The Mediating Role of Environmental Information Disclosure Quality

Environmental information disclosure quality (Eidq) refers to the breadth, specificity and verifiability of the environmental information that firms communicate to external stakeholders [45–48]. We argue that Eidq links AI to GEff through a two-step mechanism.

In the first step, AI improves Eidq. Producing high-quality environmental disclosure requires firms to collect, measure, verify and organize large amounts of dispersed environmental data. AI-enabled monitoring and energy-management systems can track emissions, energy consumption and waste in real time, reduce the cost of producing quantitative and monetized environmental indicators and improve the consistency of reporting [29,49]. AI tools are also increasingly used in the preparation and review of corporate disclosure [50]. We therefore expect AI to raise the quality of environmental disclosure.

In the second step, Eidq improves GEff through three theoretically grounded routes. The first is an information-asymmetry and signalling route. Credible disclosure reduces information asymmetry between firms and investors, lowers the cost of capital and signals environmental capability to green-oriented investors, lenders and regulators [51,52]. The resulting access to capital eases the financing of long-term, risky green R&D projects [47,53–55]. The second is a monitoring and legitimacy route. Specific and verifiable disclosure exposes firms to stakeholder scrutiny; to maintain legitimacy, managers are pressed to direct resources toward substantive green technologies [56–60]. The third is an internal feedback route. Systematically measured environmental data allow managers to identify inefficiencies in production and pollution control and to target green R&D more precisely, so that a given R&D budget yields more green technologies [61,62].

The strength of this channel depends on whether disclosure is substantive. Firms may use disclosure strategically or symbolically, and AI may lower the cost of exaggerated narratives [30,31,63–65]. Because the Eidq index used in this study rewards quantitative and monetized items more than qualitative statements, it captures the completeness and specificity of disclosure; whether disclosure reflects actual environmental performance is examined in Section 5.1. We therefore expect a positive but partial mediating effect:

H2a. *Corporate AI is positively associated with environmental information disclosure quality.*

H2b. *Environmental information disclosure quality is positively associated with green innovation efficiency.*

H2. *Environmental information disclosure quality partially mediates the positive association between corporate AI and green innovation efficiency.*

2.3. The Moderating Role of Government Subsidies

Integrating AI into green R&D requires substantial upfront investments with uncertain returns. From a resource-based perspective, government subsidies are a complementary external resource that can ease these constraints. Subsidies relieve the financial pressure associated with digital infrastructure and exploratory AI projects, share the risk of radical innovation and signal government endorsement to other resource providers [66–69]. Subsidies have been found to promote automation in small and medium-sized enterprises [66], improve R&D and recycling in the power-battery industry [70], facilitate suppliers' digital transformation [71] and enhance green innovation and productivity among AI firms [72]. Green subsidies may also curb greenwashing and encourage substantive green production [73,74]. By lowering the cost of adopting AI more deeply [75], subsidies are expected to help firms translate AI into more efficient green R&D [76,77].

However, subsidies are not randomly allocated. Firms with stronger technological capabilities or closer political ties are more likely to receive them, and subsidies may crowd out private investment or be captured by rent seeking [32,78]. These selection concerns do not alter the theoretical prediction, but they require careful empirical treatment (Section 5.2). We propose the following:

H3. *Government subsidies positively moderate the association between corporate AI and green innovation efficiency; the positive association is stronger for firms receiving higher subsidies.*

2.4. The Mediating Role of R&D Human Capital

Environmental disclosure represents an external, information-based channel. AI may also improve green innovation efficiency through an internal channel, namely, the composition of the workforce that carries out R&D. AI technologies automate routine tasks while

raising the demand for employees who can develop, adapt and apply new technologies, so firms that adopt AI tend to restructure their workforce toward technical and R&D personnel. Yao et al. [79] show that AI improves corporate production efficiency by adjusting the skill structure of the labor force, and Babina et al. [37] show that firms' AI investments rely on specialized technical human capital. We therefore expect AI to be associated with a higher share of R&D personnel.

A larger R&D workforce can in turn raise green innovation efficiency. From the resource-based view, skilled R&D personnel are a valuable and difficult-to-imitate resource that complements AI [38]. A higher share of R&D personnel also strengthens absorptive capacity, that is, the ability to recognize, assimilate and apply external knowledge [39], which is essential for green technologies that combine knowledge from engineering, materials and environmental science. When more R&D personnel are able to use AI tools for technological search, simulation and testing, a given amount of R&D expenditure is more likely to be converted into green patents. Hence, we propose the following hypotheses:

H4a. *Corporate AI is positively associated with R&D human capital.*

H4b. *R&D human capital is positively associated with green innovation efficiency.*

H4. *R&D human capital partially mediates the positive association between corporate AI and green innovation efficiency.*

Figure 1 summarizes the research framework.

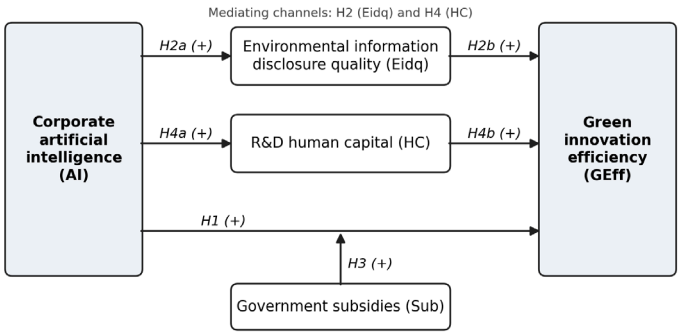


Figure 1. Research framework. Arrows indicate the hypothesized direction of influence; "(+)" denotes a hypothesized positive association.

3. Materials and Methods

3.1. Sample and Data Sources

The initial sample comprises all A-share firms listed on the Shanghai and Shenzhen stock exchanges from 2012 to 2024. The starting year reflects the period in which China's AI strategy and green innovation policies began to converge, and annual report text data on AI are more informative from 2012 onward. Financial, governance and subsidy data are obtained from the China Stock Market and Accounting Research (CSMAR) database (Shenzhen CSMAR Data Technology Co., Ltd., Shenzhen, China) and supplemented with the Chinese Research Data Services (CNRDS) database (Shanghai, China) where values are missing. Environmental disclosure data are drawn from the CSMAR environmental research database. Patent data are obtained from the China National Intellectual Property Administration (Beijing, China), and green patents are identified using the International Patent Classification (IPC) Green Inventory published by the World Intellectual Property

Organization [80]. All estimations are performed in Stata (version 17; StataCorp LLC, College Station, TX, USA) using the reghdfe and ivreghdfe commands.

We apply the following screening procedures: (1) firm-years under ST, *ST or PT status are excluded; (2) financial firms are excluded; (3) observations with missing values for the key variables, including zero or missing R&D expenditure for which GEff is undefined, are excluded; and (4) firms with fewer than three years of observations are excluded. The final sample consists of 28,219 firm-year observations for 3668 firms. All continuous variables, including those used in the supplementary analyses, are winsorized at the 1st and 99th percentiles. In fixed-effects estimations, singleton observations are automatically dropped, which explains the small differences in sample sizes between some specifications and subsamples.

3.2. Variable Definitions

3.2.1. Dependent Variable: Green Innovation Efficiency

Frontier-based approaches such as the non-radial SBM-ML index have been used to measure GEff, often with regional pollutants as undesirable outputs [10]. Such measures estimate efficiency relative to a frontier and may fail to capture firm-level heterogeneity in technological inputs [5]. Following the firm-level green input–output logic of Che et al. [5], we measure GEff as follows:

$$\mathrm{GEff}_{i,t} = \frac{\ln(1 + \mathrm{GP}_{i,t})}{\ln(\mathrm{RD}_{i,t})} \times 100 \quad (1)$$

where $\mathrm{GP}_{i,t}$ is the number of green patent applications of firm i in year t, comprising green invention patents and green utility model patents identified by the IPC Green Inventory, and $\mathrm{RD}_{i,t}$ is total R&D expenditure in RMB. The logarithmic transformation of both the numerator and the denominator reduces skewness and the sensitivity of the ratio to small denominators and to year-to-year changes in R&D expenditure. Firm-years with zero or missing R&D expenditure are excluded because the ratio is undefined, whereas firm-years without green patent applications have GEff = 0 (74.3% of the sample). The ratio is multiplied by 100 for readability. Because total R&D includes non-green activities and patents differ in technological value, we additionally use (i) separate efficiency measures based on green invention patents (GEff_Inv), which reflect substantive innovation, and green utility model patents (GEff_Uti), which reflect more incremental or strategic innovation; (ii) GEff in year $t + 1$ to allow for the lag between R&D input and patent output; (iii) an indicator of positive GEff; and (iv) two-stage DEA-SBM efficiency scores for the green R&D and green commercialization stages, constructed following Xiao et al. [81] with R&D personnel and expenditure as inputs, green patents as intermediate outputs and sales, pollution and energy-consumption indices as final outputs.

3.2.2. Independent Variable: Corporate AI

Following Yao et al. [79], we search the management discussion and analysis (MD&A) section of each annual report for 73 AI-related keywords covering AI technologies (e.g., machine learning, deep learning, computer vision and natural language processing), AI infrastructure (e.g., AI chips and cloud computing) and AI applications (e.g., intelligent manufacturing-related services and smart customer service). AI is measured as the natural logarithm of one plus the total keyword count. The AI index is not rescaled; its maximum value of 6.133 corresponds to 460 keyword occurrences ($\ln(1 + 460) = 6.133$). A one-unit increase in AI therefore corresponds to an approximately 172% ($e^1 - 1$) increase in the number of AI keywords plus one.

This text-based proxy is scalable, replicable and available for a long panel, but it captures firms' reported attention to and deployment of AI, which may differ from verified

implementation [37]. It may be upward-biased by promotional language and downward-biased when firms use AI without describing it. Because firms with stronger disclosure incentives may report more AI-related and more environmental information, we use three alternative measures: AI keyword density per 10,000 characters of MD&A text (AI_Den), which removes the influence of document length; an indicator of any AI keyword (AI_Dum); and the log count of 36 core AI technology terms that exclude broad digital terms such as big data, cloud computing and the Internet of Things (AI_Core). We also control directly for the length of the MD&A section and for Eidq. To capture AI technology development that does not depend on textual disclosure, we also use AI patents (AI_Pat), the natural logarithm of one plus the number of AI-related patent applications identified by IPC codes (Section 4.4). Because AI patents reflect firms' own AI technology development and do not capture the adoption of externally developed AI, and AI employment data are not available, we interpret all results as associations between AI and green innovation efficiency.

3.2.3. Mediating Variables: Environmental Information Disclosure Quality and R&D Human Capital

Following Kong et al. [82] and the scoring scheme of Zhao et al. [29], Eidq is constructed from 25 items in five dimensions of the CSMAR environmental research database: (1) environmental management (environmental philosophy, targets, management systems, education and training, special actions, emergency mechanisms, honors and the "Three Simultaneities" system); (2) environmental certification (ISO 14001 [83] and ISO 9001 [84]); (3) disclosure carriers (annual report, social responsibility report and environmental report); (4) environmental liabilities (wastewater, COD, SO_2, CO_2, soot and dust and industrial solid waste); and (5) environmental performance and governance (waste-gas and wastewater reduction, dust treatment, solid-waste utilization, noise, light and radiation control and clean production). For items in dimensions (4) and (5), quantitative or monetized disclosure receives 2 points, qualitative disclosure receives 1 point and no disclosure receives 0 points; for the remaining items, disclosure receives 2 points and no disclosure 0 points. Eidq equals the natural logarithm of one plus the total score. Because the index rewards specific, quantified information, it measures the completeness and specificity of disclosure; it does not verify the accuracy of the disclosed information or the underlying environmental performance [61].

R&D human capital (HC) is measured as the number of R&D personnel divided by the total number of employees (%), using the R&D investment data of listed firms in the CSMAR database (consolidated statements, periodic reports). HC data are available from 2015 onward, so the analysis of HC covers 2015–2024 (21,234 firm-years). A larger R&D workforce also raises R&D expenditure, which is the denominator of GEff; any mechanical relationship would therefore bias the association between HC and GEff downward. We nevertheless control for R&D expenditure in a robustness test (Section 5.1).

3.2.4. Moderating Variable: Government Subsidies

Government subsidies (Sub) are measured as the natural logarithm of the total amount of government subsidies recognized by the firm in the year, as reported in the notes to the financial statements in the CSMAR database; the 106 firm-years without subsidies are assigned a value of zero. As alternatives, we use the one-year lag of Sub (L.Sub), which reduces simultaneity between subsidy receipt and current innovation outcomes, and subsidies scaled by total assets (SubA, in %). To distinguish types of support, we further split total subsidies into innovation subsidies (InnoSub) and non-innovation subsidies (OthSub), each measured as the natural logarithm of one plus the amount (Section 5.2).

3.2.5. Control Variables

Following prior studies, we control for firm growth (Growth), leverage (Lev), firm age (FirmAge), firm size measured by the number of employees (Employee), the administrative expense ratio (Mfee), tangible asset ratio (Tangible) and ownership concentration (Top1). Growth captures expansion and resource-generation capacity; Lev captures financial risk and financing constraints; FirmAge and Employee capture development stage and resource endowment; Mfee, defined as administrative expenses divided by operating revenue, is an agency-cost and managerial-efficiency proxy; Tangible captures asset structure; and Top1 captures governance structure. Table 1 reports the definitions of all variables.

Table 1. Variable definitions.

Type	Symbol	Variable	Definition
Dependent	GEff	Green innovation efficiency	100 × ln(1 + green patent applications)/ln(R&D expenditure)
	GEff_Inv	Green invention efficiency	As GEff, using green invention patent applications
	GEff_Uti	Green utility model efficiency	As GEff, using green utility model applications
Independent	AI	Corporate AI	ln(1 + count of 73 AI keywords in the MD&A section)
	AI_Den	AI keyword density	AI keyword count per 10,000 characters of MD&A text
	AI_Core	Core AI technology	ln(1 + count of 36 core AI technology keywords)
Mediator	Eidq	Environmental information disclosure quality	ln(1 + total score of 25 disclosure items)
	HC	R&D human capital	R&D personnel/total employees × 100
Moderator	Sub	Government subsidies	ln(total government subsidies)
	SubA	Subsidy intensity	Government subsidies/total assets × 100
Controls	Growth	Firm growth	Growth rate of operating revenue
	Lev	Leverage	Total liabilities/total assets
	FirmAge	Firm age	ln(1 + years since establishment)
	Employee	Firm size	ln(number of employees)
	Mfee	Administrative expense ratio	Administrative expenses/operating revenue
	Tangible	Tangible asset ratio	Tangible assets/total assets
	Top1	Ownership concentration	Shareholding ratio of the largest shareholder

3.3. Model Specification

To test H1, we estimate the following two-way fixed-effects model:

$$\mathrm{GEff}_{i,t} = \alpha_0 + \alpha_1 \mathrm{AI}_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where $X_{i,t}$ is the vector of control variables, μ_i and λ_t denote firm and year fixed effects, and $\varepsilon_{i,t}$ is the error term. Standard errors are clustered at the firm level to account for serial correlation within firms. As robustness checks, we add industry-by-year and province-by-year fixed effects, which absorb time-varying industry and regional shocks such as industrial policies and local environmental regulation, and we cluster standard errors two-way by firm and year or by industry.

To test H2 and H4, we estimate the following mediation models:

$$\mathrm{Med}_{i,t} = \beta_0 + \beta_1 \mathrm{AI}_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

$$\mathrm{GEff}_{i,t} = \delta_0 + \delta_1 \mathrm{AI}_{i,t} + \delta_2 \mathrm{Med}_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

where $Med_{i,t}$ denotes the mediating variable, namely environmental information disclosure quality (Eidq) for H2 and R&D human capital (HC) for H4. The indirect effect is $\beta_1 \times \delta_2$. Complementing the causal-steps logic of Baron and Kenny [85], we test the indirect effect directly with percentile and bias-corrected bootstrap confidence intervals based on 500 firm-cluster resamples [86,87]. Partial mediation is supported if the indirect effect is significant and δ_1 remains significant.

To test H3, we mean-center AI and Sub before constructing their interaction to facilitate interpretation [88]:

$$GEff_{i,t} = \theta_0 + \theta_1 AI_{i,t} + \theta_2 \left(AI^c_{i,t} \times Sub^c_{i,t} \right) + \theta_3 Sub_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

where the superscript c denotes mean-centered variables. The marginal effect of AI on GEff is

$$\partial GEff_{i,t} / \partial AI_{i,t} = \theta_1 + \theta_2 \left(Sub_{i,t} - \overline{Sub} \right) \quad (6)$$

A significantly positive θ_2 indicates that the positive association between AI and GEff is stronger at higher subsidy levels.

3.4. Identification Strategy

The two-way fixed-effects estimates may be biased by omitted time-varying factors, measurement error in the AI proxy and reverse causality. We address these concerns in four ways. First, we use the leave-one-out mean AI of other firms in the same industry and year (AI_LOO) as an instrument. Firms in the same industry face common technological opportunities and imitation incentives, which makes the instrument relevant. Industry-level AI may, however, also affect a firm's GEff directly through technological spillovers, competition, supply-chain links or common industrial policies, which would violate the exclusion restriction [89,90]. To narrow these channels, we (i) control for the leave-one-out mean GEff of other firms in the same industry and year (GEff_Peer), which absorbs industry-level green innovation shocks and spillovers; (ii) add province-by-year fixed effects and industry-specific linear time trends; and (iii) construct an alternative instrument using only same-industry firms located in other provinces (AI_LOO_OP), which excludes local spillovers and local policies. Second, we replace the original lagged-dependent-variable test with dynamic specifications that examine whether current AI predicts future GEff and whether current GEff predicts future AI. Third, we use alternative measures of AI and GEff. Fourth, we test subgroup differences formally using pooled interaction models with firm-by-group and year-by-group fixed effects and group-specific control coefficients. Even with these tests, our design cannot rule out all sources of endogeneity; we therefore interpret the estimates as robust associations consistent with a positive effect of AI.

4. Results

4.1. Descriptive Statistics

Table 2 reports the descriptive statistics. GEff has a mean of 1.984 and a standard deviation of 3.932, and 74.3% of firm-years have no green patent applications, indicating that green innovation is concentrated in a minority of firms. GEff_Inv and GEff_Uti have means of 1.299 and 1.152, respectively. AI has a mean of 0.701, a median of 0 and a maximum of 6.133; 57.2% of firm-years contain no AI keywords in the MD&A section, and the right-skewed distribution shows that AI deployment remains concentrated in a subset of leading firms. Eidq has a mean of 1.849; HC, available from 2015 onward (21,234 firm-years), has a mean of 15.672%, indicating that R&D personnel account for about one-sixth of employees on average; and Sub has a mean of 16.511. The control variables are within ranges typical of Chinese listed firms: leverage averages 0.415, the largest shareholder holds 33.2% of shares on average and the administrative expense ratio averages 0.086.

Table 2. Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max
GEff	28,219	1.984	3.932	0.000	0.000	19.568
GEff_Inv	28,219	1.299	3.074	0.000	0.000	17.807
GEff_Uti	28,219	1.152	2.824	0.000	0.000	15.120
AI	28,219	0.701	1.004	0.000	0.000	6.133
AI_Den	28,219	1.986	5.158	0.000	0.000	114.805
AI_Core	28,219	0.305	0.654	0.000	0.000	5.226
Eidq	28,219	1.849	0.928	0.000	1.946	3.611
HC	21,234	15.672	12.449	0.350	12.940	66.880
Sub	28,219	16.511	1.826	0.000	16.560	20.271
SubA	28,219	0.590	0.655	0.000	0.384	4.006
Lev	28,219	0.415	0.197	0.038	0.406	0.910
Employee	28,219	7.730	1.171	4.174	7.640	11.181
Top1	28,219	0.332	0.144	0.075	0.309	0.758
Growth	28,219	0.149	0.393	−0.673	0.093	5.076
FirmAge	28,219	2.972	0.316	1.386	2.996	4.304
Tangible	28,219	0.922	0.088	0.442	0.953	1.000
Mfee	28,219	0.086	0.068	0.007	0.069	0.708

4.2. Baseline Regression Results

Table 3 reports the baseline results. Column (1) includes only AI and the fixed effects, and Column (2) adds the control variables. The coefficient of AI is 0.137 and significant at the 1% level ($t = 3.76$) in Column (2), supporting H1. In economic terms, a one-standard-deviation increase in AI (1.004) is associated with an increase in GEff of approximately 0.138, or 7.0% of the sample mean. Among the controls, firm size and the tangible asset ratio are positively associated with GEff, whereas the administrative expense ratio is negatively associated with it, consistent with agency costs diverting resources from efficient innovation.

Table 3. Baseline regression results.

Variable	(1) GEff	(2) GEff
AI	0.153 ***	0.137 ***
	(4.16)	(3.76)
Lev		−0.115
		(−0.57)
Employee		0.312 ***
		(5.25)
Top1		0.252
		(0.63)
Growth		−0.069 *
		(−1.80)
FirmAge		−0.007
		(−0.01)
Tangible		1.054 ***
		(3.33)
Mfee		−1.682 ***
		(−3.10)
Constant	1.877 ***	−1.356
	(72.46)	(−0.68)

Table 3. *Cont.*

Variable	(1) GEff	(2) GEff
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	28,219	28,219
R^2	0.672	0.674

Note: *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. *** and * denote significance at the 1% and 10% levels, respectively.

Table 4 examines whether the baseline result is sensitive to unobserved common shocks and to the level of clustering. Adding industry-by-year fixed effects (Column (2)), province-by-year fixed effects (Column (3)) or both (Column (4)) reduces the coefficient of AI only modestly, to between 0.106 and 0.134, and it remains significant at the 1% level. Two-way clustering by firm and year (Column (5)) and clustering by industry (Column (6)) leave the coefficient significant at the 5% and 1% levels, respectively. Time-varying industry and regional factors, such as industrial policies and local environmental regulation, therefore do not drive the baseline result.

Table 4. Robustness to high-dimensional fixed effects and alternative clustering.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.137 ***	0.106 ***	0.134 ***	0.109 ***	0.137 **	0.137 ***
	(3.76)	(2.80)	(3.67)	(2.86)	(2.77)	(3.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Absorbed	Absorbed	Absorbed	Yes	Yes
Industry × Year FE	No	Yes	No	Yes	No	No
Province × Year FE	No	No	Yes	Yes	No	No
Clustering	Firm	Firm	Firm	Firm	Firm & Year	Industry
Observations	28,219	28,126	28,215	28,122	28,219	28,219
R^2	0.674	0.685	0.679	0.691	0.674	0.674

Note: The dependent variable is GEff. Controls include Lev, Employee, Top1, Growth, FirmAge, Tangible, Mfee. Industries are defined by the CSRC industry classification (79 industries). Differences in sample sizes reflect singleton observations dropped by the fixed-effects estimator. In Column (5), *p*-values are based on 12 degrees of freedom because standard errors are clustered by firm and year, with 13 year clusters. *t*-statistics are reported in parentheses, with standard errors clustered as indicated in the Clustering row. *** and ** denote significance at the 1% and 5% levels, respectively.

4.3. Endogeneity

4.3.1. Instrumental Variable Estimation

Table 5 reports the instrumental-variable estimates. Column (1) shows that the one-period lag of AI is positively associated with current GEff (0.150, $t = 3.60$). Columns (2) and (3) use AI_LOO as the instrument. In the first stage, AI_LOO is strongly associated with firm-level AI (0.480, $t = 15.65$). The cluster-robust Kleibergen–Paap rk Wald F-statistic is 245.09 [91], far above the Stock–Yogo 10% maximal IV size critical value of 16.38 [92], so weak identification is not a concern. In the second stage, the coefficient of AI is 0.508 and significant at the 1% level.

Columns (4)–(6) address the exclusion restriction. Controlling for GEff_Peer (Column (4)) absorbs industry-level green innovation shocks and spillovers; the AI coefficient remains positive and significant (0.394, $t = 2.22$). Adding province-by-year fixed effects and industry-specific linear trends (Column (5)) yields a coefficient of 0.710 ($t = 3.24$). Using the instrument constructed from same-industry firms in other provinces (Column (6)) yields a coefficient of 0.736 ($t = 3.34$), with a first-stage coefficient of 0.486 ($t = 14.35$) and a

Kleibergen–Paap F-statistic of 205.86. The stability of the estimates across specifications that progressively remove industry-level, regional and local spillover channels suggests that the positive association is not explained by these channels. The IV estimates are larger than the fixed-effects estimates, which is consistent with attenuation bias from measurement error in the text-based AI proxy. Nevertheless, because the exclusion restriction cannot be tested directly, we interpret the IV results as supportive evidence of a positive effect.

Table 5. Instrumental variable estimation.

Variable	(1) GEff	(2) AI (First Stage)	(3) GEff (2SLS)	(4) GEff (2SLS)	(5) GEff (2SLS)	(6) GEff (2SLS)
L.AI	0.150 ***					
	(3.60)					
AI			0.508 ***	0.394 **	0.710 ***	0.736 ***
			(2.88)	(2.22)	(3.24)	(3.34)
AI_LOO		0.480 ***				
		(15.65)				
GEff_Peer				0.079 **	0.062	0.073 *
				(2.52)	(1.62)	(1.84)
Instrument	—	—	AI_LOO	AI_LOO	AI_LOO	AI_LOO_OP
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Absorbed	Absorbed
Province × Year FE	No	No	No	No	Yes	Yes
Industry trends	No	No	No	No	Yes	Yes
KP rk Wald F			245.09	239.11	231.16	205.86
Observations	23,013	28,126	28,126	28,126	28,122	28,107

Note: AI_LOO is the mean AI of other firms in the same industry and year; AI_LOO_OP is the mean AI of same-industry firms located in other provinces in the same year. GEff_Peer is the mean GEff of other firms in the same industry and year. Industry trends denote industry-specific linear time trends. KP rk Wald F is the Kleibergen–Paap rk Wald F-statistic. The first-stage coefficient of AI_LOO_OP in Column (6) is 0.486 ($t = 14.35$). t-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

4.3.2. Reverse Causality

A regression of lagged GEff on current AI would capture the association between current AI and past GEff and would be compatible with reverse causality. We therefore use two dynamic specifications, reported in Table 6. Column (1) regresses GEff in year $t + 1$ on AI in year t while controlling for GEff in year t. Current AI predicts future GEff beyond its persistence (0.134, $t = 3.53$). Column (2) reverses the direction by regressing AI in year $t + 1$ on GEff in year t while controlling for AI in year t. Current GEff does not predict future AI (0.001, $t = 0.90$). Thus, AI precedes improvements in GEff, whereas firms with stronger past green innovation efficiency do not subsequently report more AI. Because both specifications include firm fixed effects and a lagged dependent variable, the persistence coefficients are subject to Nickell bias [93]; with an average panel length of approximately eight years, this bias is limited and does not affect the asymmetry between the two directions.

Table 6. Dynamic tests of reverse causality.

Variable	(1) GEff_{t+1}	(2) AI_{t+1}
AI_t	0.134 ***	0.379 ***
	(3.53)	(34.99)
GEff_t	0.160 ***	0.001
	(10.76)	(0.90)

Table 6. *Cont.*

Variable	(1) $GEff_{t+1}$	(2) AI_{t+1}
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	23,013	23,013
R^2	0.690	0.773

Note: Controls are measured in year t. t-statistics based on standard errors clustered at the firm level are reported in parentheses. *** denotes significance at the 1% level.

4.4. Robustness Tests

Table 7 summarizes additional robustness tests. Panel A changes the sample. Excluding the COVID-19 years 2020–2022, when production and R&D activities were disrupted, yields a coefficient of 0.099 ($t = 2.30$). Excluding firms in the four municipalities directly under the central government (Beijing, Tianjin, Shanghai and Chongqing), which enjoy unusual policy resources and technological agglomeration, yields a coefficient of 0.130 ($t = 3.23$).

Table 7. Additional robustness tests.

Specification	Coefficient	t-Statistic	Observations	R^2
Panel A: Alternative samples				
Excluding 2020–2022	0.099 **	2.30	19,199	0.665
Excluding municipalities	0.130 ***	3.23	23,167	0.669
Panel B: Alternative AI measures				
AI_Den (keyword density)	0.033 ***	4.29	28,219	0.674
AI_Dum (any AI keyword)	0.080	1.58	28,219	0.673
AI_Core (core AI technologies)	0.149 ***	2.91	28,219	0.674
AI, controlling for ln(MD&A length) and Eidq	0.130 ***	3.55	28,219	0.674
Panel C: Alternative GEff measures				
GEff_Inv (green invention patents)	0.129 ***	4.29	28,219	0.650
GEff_Uti (green utility models)	0.038	1.43	28,219	0.615
GEff in year $t + 1$	0.155 ***	3.71	23,013	0.682
Indicator of GEff > 0	0.010 **	2.41	28,219	0.543
DEA-SBM green R&D efficiency	−0.001	−0.48	28,119	0.457
DEA-SBM green commercialization efficiency	0.000	0.21	28,119	0.460
Granted green patents/R&D (GEff_Grant)	0.137 ***	2.84	26,205	0.735
Granted green invention patents/R&D	0.138 ***	3.75	26,205	0.657
Green share of all patent applications (%)	0.258 *	1.95	28,144	0.576
Green share of invention applications (%)	0.415 **	2.29	28,144	0.489
Panel D: AI patents (AI_Pat)				
AI_Pat (firms covered by patent data)	1.217 ***	13.12	9366	0.700
L.AI_Pat	0.401 ***	4.33	7613	0.688
AI_Pat, industry × year and province × year FE	1.235 ***	12.73	9186	0.736
AI_Pat, uncovered firm-years set to zero	1.173 ***	12.63	28,219	0.683
AI_Pat, dependent variable GEff_Inv	1.014 ***	12.53	9366	0.673
AI_Pat, dependent variable GEff_Uti	0.522 ***	7.96	9366	0.625
AI_Pat, dependent variable GEff in year $t + 1$	0.397 ***	4.27	7613	0.688

Note: Each row reports the coefficient of the AI measure from a separate regression with controls and firm and year fixed effects. The dependent variable is GEff unless otherwise indicated. In Panel D, AI patents are identified by IPC codes following Zu et al. [94]; the sample is restricted to firms covered by the patent data except in the specification in which uncovered firm-years are set to zero. In Panel C, the measures based on granted green patents and on green patent shares use an alternative green patent dataset, and R&D expenditure for the granted-patent measures is taken from the CSMAR R&D investment data. t-statistics are based on standard errors clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Panel B uses alternative AI measures. AI keyword density (0.033, $t = 4.29$) and core AI technology terms (0.149, $t = 2.91$) are both positively and significantly associated with GEff. The AI coefficient also remains stable (0.130, $t = 3.55$) when we control for the length of the MD&A section and for Eidq, indicating that the result holds after accounting for firms' general propensity to disclose. The indicator of any AI keyword is positive but insignificant (0.080, $t = 1.58$), suggesting that GEff is associated with the intensity of AI deployment.

Panel C uses alternative GEff measures. AI is positively associated with green invention efficiency (0.129, $t = 4.29$) but not with green utility model efficiency (0.038, $t = 1.43$), indicating that the association is driven by substantive green innovation. AI is also positively associated with GEff in year $t + 1$ (0.155, $t = 3.71$) and with the probability of positive GEff (0.010, $t = 2.41$). However, AI is not significantly associated with the two-stage DEA-SBM efficiency scores. These scores measure efficiency relative to a frontier and, in the commercialization stage, also incorporate sales, pollution and energy consumption. The null results therefore limit our conclusions to the conversion of R&D into green technologies; we find no measurable association with broader frontier-based environmental–economic efficiency.

Panel C also addresses two further concerns about the GEff measure, using green patent data from an alternative patent dataset. First, because patents differ in technological value, we replace applications with granted patents, which have passed substantive examination. AI is positively associated with the efficiency of granted green patents (0.137, $t = 2.84$) and of granted green invention patents (0.138, $t = 3.75$). Second, because total R&D expenditure also funds non-green activities, we use measures that do not rely on R&D expenditure, namely the share of green patents in all patent applications and the share of green invention patents in all invention applications. AI is positively associated with both shares (0.258, $t = 1.95$; 0.415, $t = 2.29$), indicating that AI shifts the composition of firms' innovation toward green technologies. The association with the overall green share is significant only at the 10% level, whereas the evidence is stronger for invention patents, which is consistent with the results for GEff_Inv. R&D expenditure for these specifications is taken from the CSMAR R&D investment data, which cover 26,205 firm-years.

Panel D replaces the text-based index with a patent-based measure of AI technology. Following Zu et al. [94], AI patents are identified from firms' patent applications by IPC codes covering machine learning, computer vision, speech recognition, intelligent control and related fields, and AI_Pat is the natural logarithm of one plus the annual number of AI patent applications. The patent data cover 1762 listed firms, so the main estimate uses the 9366 firm-years with coverage. AI_Pat is positively associated with GEff (1.217, $t = 13.12$), and the association holds with industry-by-year and province-by-year fixed effects (1.235, $t = 12.73$), for lagged AI patents (0.401, $t = 4.33$), for GEff in year t + 1 (0.397, $t = 4.27$) and in the full sample when firm-years without coverage are set to zero (1.173, $t = 12.63$). In the covered subsample, the coefficient of the text-based index is 0.181 ($t = 2.87$) and remains significant when AI_Pat is added (0.142, $t = 2.42$), so the two measures contain distinct information. Unlike the text-based index, AI_Pat is associated with both green invention efficiency (1.014, $t = 12.53$) and green utility model efficiency (0.522, $t = 7.96$). The magnitudes should not be compared directly with the baseline, because AI patents and green patents share firms' general propensity to patent and the IPC classes used to identify AI patents are broad. We therefore treat the patent-based results as corroborating evidence that the association does not rest on textual disclosure alone.

5. Mechanism and Heterogeneity Analyses

5.1. Mediation Effects: Environmental Information Disclosure Quality and R&D Human Capital

Table 8 reports the mediation results. In Column (1), AI is positively associated with Eidq (0.021, $t = 2.64$), supporting H2a. In Column (2), Eidq is positively associated with GEff

(0.100, $t = 2.73$) after controlling for AI, supporting H2b, while the coefficient of AI remains significant (0.135, $t = 3.71$). The bootstrap indirect effect is 0.0021, with a 95% percentile confidence interval of [0.0002, 0.0047] and a bias-corrected interval of [0.0003, 0.0049], both of which exclude zero. Eidq therefore partially mediates the association between AI and GEff, supporting H2. The mediated share, however, is only approximately 1.5% of the total association, so the disclosure channel is statistically significant but economically modest; most of the association between AI and GEff operates through other channels, such as the direct improvement of R&D processes discussed in Section 2.1.

Table 8. Mediation effect of environmental information disclosure quality.

Variable	(1) Eidq	(2) GEff	(3) Eidq	(4) GEff	(5) $GEff_{t+1}$	(6) Eidq
AI	0.021 ***	0.135 ***	0.020 **		0.131 ***	
	(2.64)	(3.71)	(2.57)		(3.46)	
L.AI				0.147 ***		0.008
				(3.53)		(0.97)
Eidq		0.100 ***			0.100 ***	
		(2.73)			(2.86)	
L.Eidq				0.110 ***		
				(2.89)		
GEff			0.004 ***		0.160 ***	
			(2.72)		(10.73)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,219	28,219	28,219	23,013	23,013	23,013
R^2	0.748	0.674	0.748	0.682	0.690	0.763

Note: Bootstrap indirect effect of AI on GEff through Eidq (Column (1) AI coefficient × Column (2) Eidq coefficient) = 0.0021; 95% percentile confidence interval [0.0002, 0.0047]; 95% bias-corrected confidence interval [0.0003, 0.0049]; 500 bootstrap replications clustered by firm. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

We further address the possibility that Eidq is itself endogenous, for example because firms with stronger green innovation have greater incentives to disclose. In Column (3), AI remains positively associated with Eidq after controlling for current GEff (0.020, $t = 2.57$). In Column (4), lagged Eidq is positively associated with current GEff (0.110, $t = 2.89$), and in Column (5), current Eidq predicts GEff in year $t + 1$ after controlling for current GEff (0.100, $t = 2.86$). However, lagged AI is not significantly associated with current Eidq (0.008, $t = 0.97$; Column (6)), indicating that the AI–Eidq link is mainly contemporaneous. Taken together, the evidence supports a disclosure channel but indicates that its timing is short and its magnitude small. Moreover, because Eidq measures the completeness and specificity of disclosure, the results show that AI-related firms disclose more complete environmental information; the credibility of this information is examined below. In addition, the patent-based AI measure (Section 4.4) is not significantly associated with Eidq (0.012, $t = 1.04$). The AI–Eidq link therefore appears to be specific to text-based AI and may partly reflect a common propensity to report, which reinforces our cautious interpretation of the disclosure channel.

To distinguish the completeness of disclosure from environmental performance, we use the environmental (E) score of the Huazheng ESG rating, a third-party rating of firms' environmental performance. AI is positively associated with the E score (0.442, $t = 5.39$), also when AI is lagged (0.389, $t = 4.26$). After controlling for the E score, the association between AI and Eidq becomes weaker (0.014, $t = 1.84$, compared with 0.021 in Column (1)), suggesting that the higher disclosure quality of AI-intensive firms largely reflects better

environmental performance. Consistently, AI is negatively associated with the gap between standardized Eidq and the standardized E score (−0.040, $t = -3.12$), so AI-intensive firms do not disclose more than their environmental performance warrants. Moreover, the interaction between Eidq and the E score is positive (0.012, $t = 3.51$), indicating that disclosure is more strongly associated with GEff when it is backed by better environmental performance. Because the E score is partly based on public information, these results are supportive evidence; they suggest that the disclosure of AI-intensive firms reflects their environmental performance.

Table 9 reports the results for R&D human capital. AI is positively associated with HC (0.361, $t = 3.75$; Column (1)), supporting H4a; a one-unit increase in AI is associated with a 0.36-percentage-point higher share of R&D personnel. HC is positively associated with GEff after controlling for AI (0.020, $t = 3.71$; Column (2)), supporting H4b, and the AI coefficient declines from 0.135 in the same sample to 0.128. The bootstrap indirect effect is 0.0071, with a 95% percentile confidence interval of [0.0022, 0.0138] and a bias-corrected interval of [0.0027, 0.0149], both of which exclude zero. HC therefore partially mediates the association between AI and GEff, supporting H4. The mediated share is approximately 5.3% of the total association, more than three times that of the disclosure channel.

Table 9. Mediation effect of R&D human capital.

Variable	(1) HC	(2) GEff	(3) HC	(4) HC	(5) GEff	(6) HC_($t+1$)
AI	0.361 ***	0.128 ***	0.352 ***		0.127 ***	−0.002
	(3.75)	(3.22)	(3.68)		(3.19)	(−0.03)
L.AI				0.250 **		
				(2.37)		
HC		0.020 ***			0.017 ***	0.464 ***
		(3.71)			(3.08)	(22.78)
GEff			0.063 ***			0.009
			(3.70)			(0.73)
ln(R&D expenditure)					0.091	
					(1.63)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,206	21,206	21,206	18,227	21,206	16,695
R^2	0.901	0.709	0.901	0.903	0.709	0.933

Note: HC is the ratio of R&D personnel to total employees (%). Bootstrap indirect effect of AI on GEff through HC (Column (1) AI coefficient × Column (2) HC coefficient) = 0.0071; 95% percentile confidence interval [0.0022, 0.0138]; 95% bias-corrected confidence interval [0.0027, 0.0149]; 500 bootstrap replications clustered by firm. When ln(R&D expenditure) is controlled, the indirect effect is 0.0051 (95% percentile confidence interval [0.0012, 0.0109]). Column (6) regresses HC in year $t + 1$ on GEff in year t, controlling for HC and AI in year t. t-statistics based on standard errors clustered at the firm level are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

Several checks support this interpretation. AI remains associated with HC after controlling for current GEff (0.352, $t = 3.68$; Column (3)), and lagged AI is associated with current HC (0.250, $t = 2.37$; Column (4)), whereas current GEff does not predict HC in the following year (0.009, $t = 0.73$; Column (6)). Changes in the workforce therefore follow AI. Because a larger R&D workforce also raises R&D expenditure, the denominator of GEff, Column (5) controls for ln(R&D expenditure); HC remains positively associated with GEff (0.017, $t = 3.08$), and the indirect effect remains significant (0.0051; 95% percentile confidence interval [0.0012, 0.0109]). The results are similar with industry-by-year and province-by-year fixed effects (AI → HC: 0.362, $t = 4.09$; HC → GEff: 0.023, $t = 4.00$), and the patent-based AI measure is also positively associated with HC (0.546, $t = 3.16$). However, lagged HC is not significantly associated with current GEff when lagged AI is controlled

(0.007, $t = 1.11$), indicating that, like the disclosure channel, the human-capital channel operates mainly within the same year.

5.2. Moderating Effect of Government Subsidies

Table 10 reports the moderation results. In Column (1), the interaction between AI and Sub is positive and significant at the 1% level (0.069, $t = 4.53$), supporting H3. The main effect of Sub is also positive (0.052, $t = 4.26$). Because the variables are mean-centered, the coefficient of AI (0.122) represents the marginal effect at the mean subsidy level.

Table 10. Moderating effect of government subsidies.

Variable	(1) GEff	(2) GEff	(3) GEff	(4) GEff	(5) GEff	(6) GEff	(7) GEff
AI	0.122 ***	0.091 **	0.137 ***	0.095 **	0.138 ***	0.120 ***	0.121 ***
	(3.44)	(2.32)	(3.78)	(2.54)	(3.79)	(3.41)	(3.42)
AI × Sub	0.069 ***			0.065 ***			
	(4.53)			(4.22)			
Sub	0.052 ***			0.062 ***			
	(4.26)			(5.02)			
AI × L.Sub		0.050 ***					
		(2.97)					
L.Sub		−0.005					
		(−0.38)					
AI × SubA			0.041				
			(1.03)				
SubA			0.052				
			(1.33)				
AI × InnoSub					0.005 *		0.005 *
					(1.92)		(1.85)
InnoSub					0.005 *		0.005 *
					(1.68)		(1.73)
AI × OthSub						0.079 ***	0.079 ***
						(4.02)	(4.03)
OthSub						0.050 ***	0.049 ***
						(2.63)	(2.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Absorbed	Yes	Yes	Yes
Industry × Year FE	No	No	No	Yes	No	No	No
Province × Year FE	No	No	No	Yes	No	No	No
Observations	28,219	23,013	28,219	28,122	28,139	28,139	28,139
R^2	0.674	0.682	0.674	0.691	0.674	0.674	0.675

Note: Interaction terms are constructed from mean-centered variables. Columns (5)–(7) split total subsidies into innovation subsidies (InnoSub) and non-innovation subsidies (OthSub). With standardized subsidy measures, the interaction coefficients in a specification corresponding to Column (7) are 0.036 ($t = 1.85$) for InnoSub and 0.127 ($t = 4.03$) for OthSub; the difference is significant ($p = 0.011$). *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Figure 2 illustrates the moderating effect. Panel (a) plots the marginal effect of AI on GEff (Equation (6)) across the observed range of Sub, together with its 95% confidence interval. The marginal effect increases with subsidies; it equals 0.062 at the 25th percentile of Sub, 0.125 at the median and 0.191 at the 75th percentile, and it is positive when Sub exceeds approximately 14.74, which is close to the 10th percentile of the subsidy distribution. Panel (b) plots simple slopes, that is, the predicted change in GEff as AI increases from zero, for firms with low subsidies (25th percentile) and high subsidies (75th percentile).

The steeper line for high-subsidy firms shows that the same increase in AI is associated with a larger improvement in GEff when firms receive more government support.

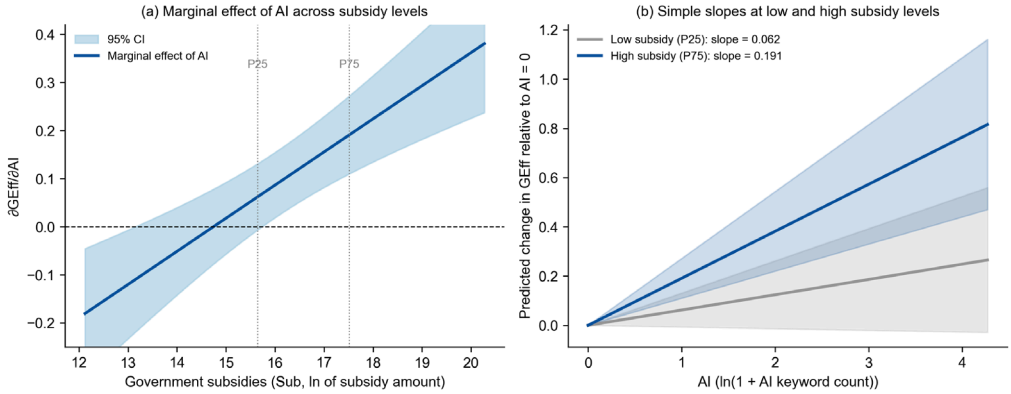


Figure 2. Moderating effect of government subsidies. (**a**) Marginal effect of AI on GEff across levels of government subsidies; the shaded area is the 95% confidence interval, and the dotted vertical lines mark the 25th and 75th percentiles of Sub; the dashed horizontal line marks a marginal effect of zero. (**b**) Simple slopes of AI at low (25th percentile) and high (75th percentile) subsidy levels; shaded areas are 95% confidence intervals. Estimates are based on Column (1) of Table 10.

Because subsidies are not randomly allocated, the interaction may partly reflect selection. Three additional tests address this concern. First, using lagged subsidies (Column (2)), which are determined before current innovation outcomes, the interaction remains positive and significant (0.050, $t = 2.97$). Second, adding industry-by-year and province-by-year fixed effects (Column (4)), which absorb time-varying industrial policies and regional subsidy programs, leaves the interaction virtually unchanged (0.065, $t = 4.22$). Third, when subsidies are scaled by total assets (Column (3)), the interaction is positive but insignificant (0.041, $t = 1.03$). This suggests that the moderating role depends on the absolute amount of resources available to finance AI integration. Overall, the results support H3, although the possibility that subsidies are directed toward firms that are better able to exploit AI cannot be completely excluded.

Because the subsidy measure aggregates different types of support, we further distinguish innovation subsidies, that is, subsidy items related to R&D and technological innovation, from all other (non-innovation) subsidies, consistent with the distinction drawn by Guo [95]. Innovation subsidies are typically allocated on the basis of technological capability and are therefore the type most exposed to the selection concern. Columns (5)–(7) of Table 10 report the results. The interaction with innovation subsidies is small (0.005, $t = 1.92$), whereas the interaction with non-innovation subsidies is larger and more precisely estimated (0.079, $t = 4.02$), and the pattern persists when both are included (Column (7)). Because the two measures have different distributions, we also standardize them: a one-standard-deviation increase in non-innovation subsidies raises the AI–GEff slope by 0.127 ($t = 4.03$), compared with 0.036 ($t = 1.85$) for innovation subsidies, and the difference is significant ($p = 0.011$). The pattern is similar with lagged subsidies (innovation: 0.009, $t = 2.36$; non-innovation: 0.072, $t = 3.29$), and among firms that receive innovation subsidies, larger amounts strengthen the association (0.041, $t = 2.25$). Thus, the moderating role of subsidies comes mainly from general financial support, and the innovation subsidies most likely to be directed toward technologically superior firms play a smaller role. This pattern is difficult to reconcile with a pure selection explanation and is consistent with subsidies easing the financial burden of AI adoption.

5.3. Heterogeneity Analysis

We examine whether the AI–GEff association differs across groups of firms. Because statistical significance within individual subsamples does not establish that coefficients differ between subsamples [34], we report, for each grouping, the subsample estimates and the results of a formal difference test. The test is based on a pooled regression in which AI and all control variables are interacted with group indicators and firm-by-group and year-by-group fixed effects are included; the coefficient of the AI × group interaction therefore equals the difference between the subsample slopes. Tables 11 and 12 report the results.

Table 11. Heterogeneity by region, pollution intensity and technology status.

Variable	(1) East	(2) Central	(3) West	(4) Heavy Pollution	(5) Non-Heavy Pollution	(6) High-Tech	(7) Non-High-Tech
AI	0.116 ***	0.164 *	0.215 *	0.146	0.128 ***	0.169 ***	0.066
	(2.73)	(1.94)	(1.71)	(1.55)	(3.23)	(3.53)	(1.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,219	4555	3429	6784	21,376	18,630	9482
R^2	0.683	0.687	0.596	0.594	0.695	0.677	0.660
Difference in AI coefficient	Base	0.048	0.099	0.018	Base	0.103	Base
p-value of difference	—	0.609	0.454	0.859	—	0.152	—
Joint test *p*-value	0.695						

Note: Difference tests are based on pooled regressions in which AI and all controls are interacted with group indicators and firm-by-group and year-by-group fixed effects are included, with standard errors clustered by firm. Subsample sizes exclude singleton observations (16 for the regional, 59 for the pollution and 107 for the high-tech groupings). *t*-statistics are reported in parentheses. *** and * denote significance at the 1% and 10% levels, respectively.

Table 12. Heterogeneity by life cycle, industry and ownership.

Variable	(1) Growth	(2) Mature	(3) Decline	(4) Manufacturing	(5) Non-Manufacturing	(6) SOE	(7) Non-SOE
AI	0.135 **	0.086	0.156 *	0.169 ***	0.047	0.133 *	0.124 ***
	(2.29)	(1.40)	(1.92)	(3.63)	(0.77)	(1.80)	(3.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,015	10,338	4560	21,154	6982	8550	19,603
R^2	0.710	0.729	0.754	0.668	0.705	0.689	0.677
Difference in AI coefficient	Base	−0.049	0.021	0.123	Base	0.008	Base
p-value of difference	—	0.531	0.835	0.108	—	0.921	—
Joint test *p*-value	0.725						

Note: Life-cycle stages follow the cash-flow classification of Dickinson [96]. Difference tests are constructed as in Table 11. Subsample sizes exclude singleton observations dropped by the fixed-effects estimator. *t*-statistics based on standard errors clustered at the firm level are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

5.3.1. Regional Heterogeneity

Based on the classification of the National Bureau of Statistics, we divide firms into eastern, central and western regions. The AI coefficient is 0.116 ($t = 2.73$) in the east, 0.164 ($t = 1.94$) in the central region and 0.215 ($t = 1.71$) in the west. Although the point estimates are larger in the central and western regions, the differences relative to the east are not significant (central−east = 0.048, $p = 0.609$; west−east = 0.099, $p = 0.454$; joint $p = 0.695$).

The lower significance levels in the central and western regions reflect their smaller samples and larger standard errors. Hence, the data do not support a stronger association in any region. The three subsample sizes sum to 28,203 because 16 singleton observations are dropped in the subsample regressions.

5.3.2. Heavily Polluting Industries

Following China's classification of heavily polluting industries for listed firms, the AI coefficient is 0.146 ($t = 1.55$) for heavily polluting firms and 0.128 ($t = 3.23$) for other firms. The difference is close to zero and insignificant (0.018, $p = 0.859$). The insignificant coefficient for heavily polluting firms reflects limited precision and does not indicate that AI is ineffective in these firms. Their point estimate is slightly larger than that of other firms, and its 95% confidence interval $[-0.038, 0.330]$ contains the full-sample estimate. AI adoption is much less common among heavily polluting firms: only 22.7% of their firm-years mention any AI keyword, compared with 49.2% of other firm-years, and the within-firm standard deviation of AI is 0.43, compared with 0.61. With fewer observations and less variation in AI, the standard error for heavily polluting firms is more than twice as large (0.094 versus 0.040). Within this group, AI is positively associated with R&D human capital (0.478, $t = 2.82$) but not with Eidq (-0.001, $t = -0.05$), possibly because heavily polluting firms are subject to mandatory environmental disclosure requirements that leave less room for discretionary improvement. Thus, there is no evidence that the association differs by pollution intensity, and the low level of AI adoption among heavily polluting firms suggests considerable room for AI to support their green innovation.

5.3.3. High-Tech Enterprises

The AI coefficient is 0.169 ($t = 3.53$) for certified high-tech enterprises and 0.066 ($t = 1.23$) for other firms. The point estimate is larger for high-tech enterprises, consistent with their greater absorptive capacity [39], but the difference is not significant (0.103, $p = 0.152$).

5.3.4. Corporate Life Cycle

A firm's life-cycle stage shapes its resources, strategic priorities and capacity to absorb new technologies [96,97]. Following Dickinson [96], we classify firm-years by the signs of net operating, investing and financing cash flows reported in the CSMAR cash flow statements. As is common for listed firms, introduction and growth firms are combined into the growth stage, and shake-out and decline firms are combined into the decline stage. The AI coefficient is 0.135 ($t = 2.29$) for growth-stage firms, 0.086 ($t = 1.40$) for mature-stage firms and 0.156 ($t = 1.92$) for decline-stage firms. Neither the mature–growth difference (-0.049, $p = 0.531$) nor the decline–growth difference (0.021, $p = 0.835$) is significant (joint $p = 0.725$). An alternative composite classification based on the industry–year ranks of revenue growth, the capital expenditure ratio and (inverse) firm age leads to the same conclusion (joint $p = 0.175$). Hence, the association between AI and GEff does not vary systematically over the corporate life cycle.

5.3.5. Industry: Manufacturing and Non-Manufacturing Firms

Because green patents are concentrated in manufacturing, we compare manufacturing and non-manufacturing firms. The AI coefficient is 0.169 ($t = 3.63$) for manufacturing firms and 0.047 ($t = 0.77$) for non-manufacturing firms, but the difference is not significant (0.123, $p = 0.108$). The industry-by-year fixed-effects estimates in Table 4 further show that the baseline association does not depend on differences across the 79 industries.

5.3.6. Ownership

The AI coefficient is 0.133 ($t = 1.80$) for state-owned enterprises (SOEs) and 0.124 ($t = 3.06$) for non-SOEs, and the difference is insignificant (0.008, $p = 0.921$).

Overall, the heterogeneity analyses indicate that the positive association between AI and GEff is broadly similar across regions, pollution intensity, technology status, industries, ownership and life-cycle stages. This homogeneity is itself informative: the benefits of AI for green innovation efficiency are not confined to particular regions or types of firms.

6. Discussion

The positive association between AI and GEff is consistent with studies of energy firms, rare earth enterprises and AI pilot zones [24–26,28]. Our evidence extends these findings in three respects. First, it is based on the full population of listed firms and is robust to industry-by-year and province-by-year fixed effects, so it does not depend on the characteristics of a single industry or region. Second, the association is driven by green invention patents and by the intensity of AI use. This pattern suggests that AI is associated with substantive green technological progress, a conclusion reinforced by the positive association between AI patents and GEff. This evidence speaks to concerns that AI may mainly encourage strategic innovation [64]. Third, the absence of an association with DEA-SBM efficiency scores indicates that the benefits of AI are concentrated in the conversion of R&D into green technologies and do not yet extend measurably to frontier-based environmental–economic efficiency, which also depends on commercialization, pollution and energy outcomes.

The disclosure channel is statistically significant but small, which helps reconcile the optimistic view that AI improves environmental transparency [29] with concerns about AI-enabled greenwashing [30,31]. AI does raise the completeness of environmental disclosure, and more complete disclosure is associated with higher subsequent GEff, but this route explains only a small fraction of the AI–GEff association. Third-party environmental ratings further suggest that the additional disclosure of AI-intensive firms is backed by environmental performance. Most of the association is likely to operate through internal channels, such as faster technological search and more efficient R&D processes.

The human-capital channel complements the disclosure channel. Whereas Eidq captures an external, information-based route, HC captures an internal route: AI is associated with a shift in the workforce toward R&D personnel, and this shift is associated with more green patents per unit of R&D expenditure. This finding is consistent with evidence that AI changes the skill structure of the labor force [79] and that its benefits depend on complementary technical human capital [37], and it helps explain why the association between AI and GEff is concentrated in green invention patents, which require more specialized knowledge than utility models. Nonetheless, both mediated shares are modest, so much of the association between AI and GEff is likely to operate through other channels, such as AI-enabled technological search and testing within existing R&D teams.

Finally, the formal heterogeneity tests caution against a common practice in the literature, namely inferring heterogeneous effects from differences in significance levels across subsamples [34]. Once differences are tested directly, the association between AI and GEff appears broadly homogeneous. Larger point estimates for central and western firms, high-tech enterprises and manufacturing firms may indicate economically meaningful differences, but larger samples or more precise measures are needed to establish them.

7. Conclusions

7.1. Main Conclusions

Using panel data on Chinese A-share listed firms from 2012 to 2024, this study examines the relationship between corporate AI and green innovation efficiency. Four conclusions emerge. First, AI is positively and robustly associated with GEff, mainly through green invention patents. The association survives high-dimensional fixed effects, leave-one-out instrumental variables that account for industry-level green innovation shocks, alternative measures including AI patents and dynamic tests showing that past GEff does not predict future AI. Second, environmental information disclosure quality and R&D human capital partially mediate this association; the human-capital channel is larger, but both mediated shares are modest. Third, government subsidies strengthen the association, including when lagged subsidies and high-dimensional fixed effects are used, and this moderating role stems mainly from non-innovation subsidies. Fourth, the association does not differ significantly across regions, pollution intensity, technology status, industries, ownership or life-cycle stages. Because the main AI measure is based on annual report text and the identification strategy relies on assumptions that cannot be fully tested, these findings should be interpreted as robust associations consistent with a positive effect of AI.

7.2. Policy Implications

First, firms can integrate AI into green R&D processes, such as technological search, virtual testing and energy and emission monitoring; our results indicate that the intensity of AI deployment is associated with more efficient green innovation. Second, firms and regulators should strengthen the specificity and verifiability of environmental disclosure. Because AI mainly increases the completeness of disclosure, regulators should complement disclosure requirements with third-party assurance and penalties for misleading statements to ensure that more complete disclosure also becomes more credible. Third, because the moderating role of subsidies stems mainly from general support, governments can help firms bear the cost of integrating AI into green R&D, for example by co-financing digital infrastructure and AI-enabled environmental monitoring, while using transparent, performance-based allocation rules to reduce selection and rent seeking. Fourth, firms should pair AI adoption with investment in R&D personnel and training, because the association between AI and green innovation efficiency partly operates through the expansion of the R&D workforce. Because the AI–GEff association is broadly homogeneous across firm types, such policies need not be confined to high-tech firms or developed regions. In particular, AI adoption remains limited among heavily polluting firms although their estimated association is similar to that of other firms, so encouraging AI-enabled emission monitoring and green R&D in these industries may help improve their green innovation efficiency.

7.3. Limitations and Future Research

This study has several limitations. First, the AI measure is based on keyword frequency in the MD&A section of annual reports. It captures disclosed attention to and deployment of AI, which may differ from verified implementation, and it may be affected by reporting conventions. Although a patent-based measure corroborates the main results, AI patents capture firms' own AI technology development and miss the adoption of externally developed AI, the patent data do not cover all firms, and the IPC classes used to identify AI patents are broad. Future research could use AI investment or AI-skilled employment to measure actual adoption more directly. Second, GEff relates green patent applications to total R&D expenditure, which includes non-green R&D. Although the results hold for granted green patents and for the green share of patent applications, which does not rely on R&D expenditure, patent counts do not fully capture technological value; future studies

could use green R&D expenditure, citation-weighted green patents or reconstructed frontier measures. Third, Eidq measures the completeness and specificity of disclosure, and its credibility is harder to assess. Third-party environmental ratings suggest that the disclosure of AI-intensive firms is backed by environmental performance, but these ratings partly rely on public information; linking disclosure to independently verified environmental performance would help distinguish substantive from symbolic disclosure. Fourth, the sample is limited to Chinese listed firms, and cross-national comparisons would help assess the external validity of the findings. Finally, a standardized measure of generative AI is not yet available; examining how generative AI differs from earlier AI technologies in its relationship with green innovation is a promising direction for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CNRDS	Chinese Research Data Services Platform
CSMAR	China Stock Market & Accounting Research Database
DEA-SBM	Data envelopment analysis–slacks-based measure
Eidq	Environmental information disclosure quality
FE	Fixed effects
GEff	Green innovation efficiency
HC	R&D human capital
IPC	International Patent Classification
IV	Instrumental variable
MD&A	Management discussion and analysis
R&D	Research and development
SOE	State-owned enterprise
Sub	Government subsidies
2SLS	Two-stage least squares

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