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Artificial Intelligence Capability and Corporate Green Innovation: The Role of Knowledge Fusion and Technology Cooperation

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Abstract

This paper examines the relationship between firms' artificial intelligence (AI) capability and corporate green innovation and the potential channels underlying this relationship. Using a firm-year panel of Chinese A-share firms listed on the Shanghai and Shenzhen main boards from 2002 to 2024, we find that stronger AI capability is positively associated with green innovation output, citation-based green innovation impact, and green technological knowledge breadth. Further mechanism analyses provide evidence consistent with knowledge fusion and formal technology cooperation as two potential channels. Specifically, stronger AI capability predicts greater technological overlap between firms' AI and green patent portfolios and broader formal green technology cooperation in the subsequent year, including inter-firm cooperation and industry–university–research collaboration. Overall, the findings suggest that AI capability may help shape the knowledge generation and collaborative development processes of green innovation, potentially contributing to greater green innovation output, impact, and knowledge breadth.

Keywords: artificial intelligence capability; green innovation; knowledge fusion; technology cooperation; green patents

1. Introduction

Artificial intelligence (AI) is becoming an important technological force that reshapes firms' innovation activities. As an emerging general-purpose technology, AI can improve firms' information processing, knowledge search, and resource allocation capabilities [1–3]. Meanwhile, the green and low-carbon transition requires firms to continuously engage in green technology R&D to address energy constraints, environmental regulation, and sustainability pressures. Against this background, an important question arises: Can firms' AI capability be transformed into green innovation performance? In which aspects of green innovation will this effect be reflected? More importantly, through what mechanisms does AI capability empower corporate green innovation?

Recent studies provide important evidence on the green innovation effects of AI. By examining the effects of managerial AI attention or AI adoption [4–7] and the implementation of AI-related policies [8–10] on green innovation, most studies document a positive relationship between AI and corporate green innovation. These studies further explore the mechanisms underlying the AI-green innovation relationship from the perspectives of governance [4,6,10], resource inputs [7,8], and innovation capability [6,8,11]. Building on

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this literature, three issues merit further examination. First, managerial AI attention and AI policy exposure mainly reflect firms' disclosed attention or external policy environments, and may not fully capture firms' substantive AI technological accumulation. Second, given that AI is a general-purpose and recombinable technology, the knowledge boundaries and subsequent impact of innovation outcomes are important dimensions in studying AI-enabled innovation. Yet in current AI and green innovation research, green innovation is still often measured by the number of green patents, or only roughly distinguished by patent type or grant status. Finally, existing explanations of the mechanisms through which AI affects green innovation focus more on conditional channels such as governance improvement and resource allocation, while paying less attention to whether AI reshapes the knowledge generation and collaborative development processes of green innovation.

To examine these issues, this paper studies Chinese A-share firms listed on the Shanghai and Shenzhen main boards and constructs a firm-year panel from 2002 to 2024. Specifically, using patent data from the China National Intellectual Property Administration (CNIPA), we construct a patent-based measure of firms' AI technological accumulation, AI Capability, as the natural logarithm of one plus the number of AI patent applications filed by the listed firm and its subsidiaries. We capture corporate green innovation from three dimensions: green innovation output (GreenPatents), green innovation impact (GreenImpact), and green knowledge breadth (GreenBreadth). The baseline estimates show that higher lagged AI Capability is positively associated with green patent output, green innovation impact, and green knowledge breadth, with coefficients of 0.384, 0.220, and 3.764, respectively, all significant at the 1% level. The results remain robust to alternative AI measures based on AI-related hiring and MD&A text, which capture firms' demand for AI-related human capital and disclosed strategic attention to AI, respectively. The estimates also remain positive and significant after removing patents jointly classified as AI and green and reconstructing the outcome measures. Finally, the staggered pilot-zone analysis provides complementary identification evidence, with AI Capability responding before the green innovation outcomes become more pronounced.

To examine the channels underlying the baseline relationship, we focus on knowledge fusion and technology cooperation. We employ a strict temporal sequence, linking $AI\ Capability_{t-2}$ to the mechanism variables at $t-1$ and green innovation at t, to reduce concerns about contemporaneous correlation and reverse causality. Knowledge fusion is measured by the overlap between the four-character IPC classes covered by firms' AI and green patent portfolios. We further use the Jaccard index, Binary Cosine, and Excess Overlap Z-score to adjust for differences in the sizes of the two IPC sets. Technology cooperation is measured using the breadth of external partners in green patent co-applications, with external firms and universities or research institutions examined separately. Across these measures, higher AI Capability predicts greater subsequent knowledge fusion and technology cooperation, which are in turn positively associated with all three green innovation outcomes. Formal indirect-effect tests based on Sobel tests and firm-cluster bootstrap confidence intervals provide further evidence consistent with these two proposed channels.

This paper contributes to the literature in three ways. First, it complements studies using managerial AI attention, AI adoption, or policy exposure by measuring firms' patent-based technological accumulation in AI. This countable and verifiable measure captures AI-related technological knowledge output at a fine-grained firm level. Second, it examines corporate green innovation across three dimensions: output, technological impact, and knowledge breadth. By distinguishing the number of green patents, highly cited green patents, and the scope of IPC classes covered, this multidimensional framework moves beyond patent counts and provides a more differentiated assessment of green innovation outcomes. Third, it extends research on the channels linking AI capability and

green innovation by providing patent-based evidence consistent with knowledge fusion and formal technology cooperation as two potential channels.

The rest of the paper proceeds as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data, variables, and model specification. Sections 4–6 report the main empirical results, mechanism tests, and heterogeneity analysis, respectively. Section 7 concludes.

2. Literature Review and Hypothesis Development

2.1. Artificial Intelligence Capability and Green Innovation

AI is becoming an important technological force that shapes firms' innovation activities. Compared with traditional information technologies, AI places greater emphasis on recognition, prediction, learning, and decision support based on data, algorithms, and computing power. It may therefore change how firms identify technological opportunities, process complex information, and allocate R&D resources [2,3]. At the firm level, AI capability reflects firms' technological accumulation in AI and provides a knowledge base for technological search, technology development, and problem solving. Thus, AI capability may constitute an important technological foundation for complex innovation activities.

Green innovation differs from general innovation in several respects. Green technology development often faces multiple constraints related to technological feasibility, environmental performance, and economic returns. It is therefore characterized by greater uncertainty and longer payback periods. In addition, green technologies involve multiple domains, such as energy use, pollution control, resource recycling, and low-carbon production, requiring firms to integrate diverse knowledge sources and continuously identify external technological opportunities. Prior studies show that green technologies rely more heavily on complex knowledge combinations and external knowledge sources than non-green technologies, and that they generate substantial knowledge spillovers [12,13]. Against this background, AI capability may reduce the uncertainty of green innovation by improving information-processing efficiency, expanding the boundary of technological search, and strengthening prediction and experimentation in the R&D process. However, AI technological accumulation does not automatically translate into green innovation. Its effective use may require complementary resources and organizational adaptation, while digital technology adoption can increase energy use and infrastructure demand through equipment operation and large-scale data processing [14].

The growing literature examines the relationship between AI-related activities and corporate green innovation. Some studies use annual reports or MD&A texts to measure firms' AI adoption or AI attention, and document positive associations between AI adoption and green innovation efficiency and output [4,5]. Other studies examine intelligent manufacturing, intelligent transformation, or AI pilot policies, including through quasi-natural experiments, and report positive effects on the quantity and quality of corporate green innovation [8–10]. Patent-based studies further suggest that AI is increasingly embedded in green technological systems, and that AI-enabled green patents or AI-green technologies tend to have greater technological impact, originality, or breakthrough potential [15,16].

Although converting AI technological accumulation into green innovation requires complementary resources and organizational adaptation, its potential to improve technological search, information processing, and experimentation leads us to expect an overall positive relationship across the three dimensions of green innovation examined in this study. We therefore propose the following hypothesis:

Hypothesis 1. *Firms with stronger AI capability exhibit higher levels of green innovation.*

2.2. Knowledge Fusion Mechanism

Innovation is essentially a process of searching for, absorbing, recombining, and reusing existing knowledge. The absorptive capacity view argues that firms' ability to recognize, assimilate, and apply external knowledge is an important source of innovative capability [17]. The technology recombination perspective further suggests that breakthrough innovation often arises from new combinations of different technological components and knowledge elements, although recombination also increases complexity and coordination costs [18,19]. Whether firms can develop effective recombinant capabilities depends on their existing knowledge structures, intraorganizational networks, and ability to connect knowledge across domains [20,21].

Green innovation often requires the integration of knowledge across technological domains. Compared with general technological innovation, green innovation often needs to address multiple objectives, including production efficiency, environmental governance, energy conservation, and resource recycling, and its technological paths frequently span multiple knowledge domains. Prior studies show that green technologies are more complex and novel than non-green technologies, and rely more heavily on diverse knowledge sources and knowledge recombination processes [12]. Green technologies also generate strong knowledge spillovers, reflected not only in direct patent citations but also in the diffusion of knowledge to broader downstream technological fields [13]. Firms' green innovation performance may therefore depend not only on investment in green technologies, but also on their ability to integrate knowledge from different technological domains.

AI capability may provide a technological foundation for knowledge fusion in green innovation. By supporting recognition, prediction, and pattern discovery, it may help firms process technical, patent, production, and environmental information, identify connections across technological fields, and reduce the costs of cross-domain knowledge search and matching. However, these benefits are not automatic: technological distance between AI and green knowledge may increase integration and coordination costs, particularly when firms lack sufficient absorptive and recombinant capabilities.

Prior research suggests that AI may affect not only final products and services, but also the innovation process itself as a method of invention [3]. In the green technology domain, Biggi et al. [15] develop the concept of green intelligence and show that AI algorithms are being applied to green technologies, with AI-green technologies exhibiting stronger technological impact, originality, and generality. Based on patent data, Volpentesta et al. [16] also find that AI-enabled green patents have higher technological influence and greater breakthrough potential. Together, these studies show that AI is increasingly embedded in green technological development. We therefore expect AI capability to facilitate the integration of AI-related and green technological knowledge and thereby support firms' green innovation. We propose the following hypothesis:

Hypothesis 2. *AI capability promotes corporate green innovation by strengthening knowledge fusion between AI technologies and green technologies.*

2.3. Technology Cooperation Mechanism

Green innovation often extends beyond organizational boundaries. Because green technology development combines knowledge from multiple domains, firms may use technology cooperation to access external knowledge, share R&D risks, and acquire complementary resources. Prior studies show that knowledge relatedness in external collaboration networks affects firms' ability to absorb external knowledge and build innovation capability, while industrial collaboration networks can promote high-quality innovation by providing heterogeneous knowledge and complementary resources [22,23]. In the context of green in-

novation, green technology cooperation networks improve ecological innovation efficiency, suggesting that cooperative relationships play an important role in green knowledge flows and technology diffusion [24]. Research on supply-chain cooperation further shows that green customer and supplier integration improves firms' green innovation performance, and that the effects of green R&D cooperation depend on technological spillovers, coordination mechanisms, and partner relationships [25,26]. Thus, technology cooperation may support green innovation by expanding firms' access to external knowledge and complementary resources.

AI capability may strengthen firms' ability to engage in green technology cooperation. AI can help firms process patent texts, technical documents, supply-chain information, and market demand data, thereby allowing them to identify cooperation opportunities and technological complementarities more effectively and reduce the costs of information search, partner matching, and knowledge coordination in cross-organizational R&D. At the same time, stronger AI capability may allow firms to internalize R&D tasks that would otherwise require external expertise, while coordination and knowledge-appropriation risks may further discourage collaboration. Its effect on technology cooperation therefore depends on whether these forces outweigh the gains from accessing complementary external knowledge.

Existing research finds that AI adoption affects firms' open innovation strategies and their use of external innovation resources [27]. In the green innovation context, intelligent transformation may promote green innovation through cooperation channels [7]. This cooperative effect may also unfold through supply-chain relationships and industry–university–research collaboration: customer AI capability can affect supplier green innovation through knowledge transfer, collaborative innovation, and supply-chain governance, while industry–university–research digital innovation collaboration helps promote AI-driven green innovation [28,29]. Given the cross-domain nature of green technology and its reliance on heterogeneous knowledge, the knowledge required for green innovation is unlikely to be fully internalized through AI accumulation alone. We therefore expect firms with stronger AI capability to engage in broader green technology cooperation, which may in turn support green innovation. We propose the following hypothesis:

Hypothesis 3. *AI capability promotes corporate green innovation by strengthening technology cooperation in green innovation activities.*

3. Empirical Strategy

3.1. Data and Sample

We use Chinese A-share firms listed on the Shanghai and Shenzhen main boards as the research sample and construct a firm-year panel covering 2002 to 2024. The data come from several sources. First, patent and patent citation data are obtained from CNIPA. Second, the annual report text data used to construct alternative AI measures are collected from CNINFO (www.cninfo.com.cn), the official disclosure platform designated by the China Securities Regulatory Commission (CSRC). Third, job-posting data used to construct the AIHiring measure are publicly collected from major Chinese recruitment-information platforms (The recruitment data cover 51job, BOSS Zhipin, Zhaopin, Liepin, Lagou, and Kanzhun). Finally, listed firms' basic information, financial data, and governance data are obtained from the China Stock Market and Accounting Research (CSMAR) database. We aggregate and merge these data at the firm-year level. Patent-based variables are constructed at the scope of listed firms and their subsidiaries.

We then apply the following sample filters. First, we retain only firms listed on the Shanghai and Shenzhen main boards. Second, we remove firm-year observations for ST/PT

firms during the sample period. Third, we exclude firms in the financial industry. Fourth, we drop observations with missing control variables. In addition, all continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of extreme values. Because patent count variables are highly right-skewed and include many zero values, we use the natural logarithm of one plus the patent count, which reduces the influence of extreme observations while retaining firm-year observations with zero patents. Finally, to mitigate concerns about reverse causality, all right-hand-side variables are lagged by one year. The final baseline regression sample contains 29,136 firm-year observations for 2407 listed firms.

3.2. Main Variables

3.2.1. AI Capability

This paper uses patent-based AI Capability as the core explanatory variable to capture firms' technological accumulation in AI. We aggregate AI patent applications filed by the listed firm and its subsidiaries in a given year to the listed firm-year level and measure AI Capability as the natural logarithm of one plus this total number of AI patent applications. AI patents are identified following Qiao and Qian [30] and Yao et al. [31]. Specifically, we use the AI dictionary developed by Yao et al. [31] to identify whether patent titles and abstracts contain AI-related keywords. This dictionary has been widely used in China-based AI studies, such as Chen et al. [7] and Pan et al. [32]. The full AI keyword dictionary is provided in Supplementary Table S2. We further supplement this text-based identification using the international patent classification codes for AI patents provided in the *Key Digital Technology Patent Classification System (2023)* issued by the CNIPA Office in 2023 [33]. A patent is classified as an AI patent if it satisfies either the keyword-based criterion or the classification-code criterion.

We use the patent-based measure for three considerations. First, patent applications provide an observable and verifiable record of AI-related technological knowledge output and are less directly influenced by differences in corporate disclosure styles. Second, patent-based AI measures provide a countable and verifiable firm-level measure of AI technological accumulation at a finer granularity. Third, the technological classifications and applicant information contained in patent records provide a common empirical basis for examining the knowledge-fusion and technology-cooperation channels.

In the robustness checks, we consider four additional AI measures. First, Any_AI indicates whether the listed firm or any of its subsidiaries files at least one AI patent application in a given year, capturing the presence rather than the volume of AI patenting activity. Second, the MD&A-based AI measure applies the 73-item AI keyword dictionary developed by Yao et al. [31] to the management discussion and analysis sections of firms' annual reports, capturing firms' disclosed attention to AI. Third, AIHiring applies the same dictionary to job-posting texts and is measured as the natural logarithm of one plus the number of deduplicated AI-related job postings matched to the listed firm and its subsidiaries. This measure captures firms' recruitment demand for AI-related human capital. Fourth, AI patent stocks use depreciation rates of 10%, 15%, and 20% to address the concern that annual patent applications capture a flow rather than accumulated technological capability. These measures provide complementary proxies based on patenting presence, corporate disclosure, labor demand, and accumulated patent stocks.

3.2.2. Green Innovation

Green patents are identified according to the IPC Green Inventory released by the World Intellectual Property Organization (WIPO) in 2010 [34] and are matched to listed firms and their subsidiaries based on patent-applicant information. To address concerns about strategic

green patenting and quantity-quality divergence raised in recent studies [35–37], we measure green innovation from three complementary dimensions: quantity, technological impact, and knowledge breadth.

Green innovation quantity, denoted as GreenPatents, is measured as the natural logarithm of one plus the number of green patent applications filed by a firm and its subsidiaries in a given year. Green innovation impact, denoted as GreenImpact, is measured as the natural logarithm of one plus the number of high-impact green patents. A green patent is classified as high-impact if it receives at least one forward citation within two years after application and its two-year forward-citation count falls within the top 10% of green patents filed in the same application year. This application-year-specific threshold accounts for differences in citation opportunities across patent cohorts. Finally, following Yang and Hu [11] and Akcigit et al. [38], GreenBreadth measures green knowledge breadth as the number of distinct four-character IPC classes covered by a firm's green patents in a given year. Together, these indicators capture the output, subsequent technological influence, and knowledge scope of corporate green innovation.

In the robustness checks, we use several alternative green innovation outcomes. GreenInv is the natural logarithm of one plus the number of green invention patent applications, while GreenGrant is the natural logarithm of one plus the number of granted green patents. GreenInvShare is the ratio of green invention patent applications to all green patent applications, and KnowDiv is one minus the Herfindahl index of four-character IPC-class shares among a firm's green patents. We further assess the measurement of green innovation impact using a three-year citation window, total forward-citation counts, and corresponding measures that exclude identifiable self-citations. These alternative outcomes examine whether the findings depend on patent type, grant status, innovation composition, knowledge diversity, citation horizon, or self-citation.

3.2.3. Mechanism Variables

Knowledge fusion. We construct the knowledge fusion variable, KnowFusion, based on the four-character IPC classes covered by firms' AI and green patent portfolios. Specifically, KnowFusion is calculated as the number of four-character IPC classes shared by the two portfolios. This measure captures the extent to which firms' AI technological knowledge intersects with their green technological knowledge. If firms embed their accumulated AI knowledge in green R&D processes, their AI and green patents should exhibit greater overlap in technological classifications. Because this raw overlap count may increase with the sizes of the two IPC sets, we also construct three normalized measures. The Jaccard index divides the overlap by the union of the two sets, Binary Cosine divides it by the geometric mean of their sizes, and the Excess Overlap Z-score compares the observed overlap with the level expected given the two set sizes and the annual IPC-class universe.

Technology cooperation. We measure green technology cooperation using green-patent co-application data. After excluding any co-applicant matched to the focal listed firm or one of its subsidiaries, we remove repeated partner names within each firm-year. TechCoop is the natural logarithm of one plus the number of distinct external partners, capturing the breadth of a firm's cross-organizational cooperation in green innovation. We further classify external partners as firms (FirmCoop) or universities and research institutions (UnivCoop) using organization-name keywords (University/research partners are identified using keywords including "university," "college," "research institute," "institute," "academy of sciences," "laboratory," "engineering center," "technology center," and "scientific research" in Chinese organization names. Firm partners are identified using keywords including "company," "group," "factory," "limited," "shareholding," "enterprise," "bank," "securities," "insurance," and "cooperative" in Chinese organization names). Since

affiliated corporate research institutes commonly contain both research-related and corporate legal-form terms, the hierarchical classification gives priority to corporate legal-form indicators. FirmCoop and UnivCoop are the natural logarithm of one plus the number of distinct partners of the corresponding type.

We further construct three alternative measures to capture complementary dimensions of technology cooperation. CoopIntensity measures cooperative activity intensity as the natural logarithm of one plus the number of green patent applications involving at least one external partner. RepeatCoop captures repeated cooperation by counting current external partners that appeared in any earlier year, while ContinuingCoop captures cooperation continuity by counting current external partners that also appeared in the immediately preceding year. Both measures are transformed using the natural logarithm of one plus the corresponding count.

3.2.4. Control Variables

To account for observable firm-level characteristics associated with AI Capability and green innovation, this paper follows prior studies on AI adoption and corporate green innovation and controls for a set of financial characteristics, governance variables, and firm attributes [5,36]. Specifically, the control variables include firm size (Size), leverage (Leverage), return on assets (ROA), operating cash flow (CashFlow), Tobin's Q (TobinQ), firm age (FirmAge), CEO-chair duality (Duality), the shareholding ratio of the top ten shareholders (Top10), state ownership (SOE), and revenue growth (Growth). Consistent with the core explanatory variable, all firm-level control variables are lagged by one year in the baseline regressions. Continuous variables are winsorized by year at the 1st and 99th percentiles. Detailed variable definitions are provided in Supplementary Table S1.

3.2.5. Descriptive Statistics

Table 1 reports descriptive statistics for the 29,136 firm-year observations in the baseline regression sample. Green innovation variables show substantial cross-firm variation. Specifically, GreenPatents has a mean of 1.063 and a median of 0.693. GreenImpact has a mean of 0.307 and a median of 0, suggesting that high-impact green patents are concentrated among a subset of sample firms. GreenBreadth has a mean of 4.708 and a standard deviation of 9.921, indicating marked heterogeneity in the knowledge scope of firms' green innovation. The core explanatory variable, AI Capability, has a mean of 0.814 and a median of 0, suggesting that AI patenting activity is strongly right-skewed and that firms differ substantially in their AI technological accumulation. For the control variables, the average leverage ratio is 0.448, the average ROA is 0.043, and state-owned enterprises account for about 47.3% of the firm-year observations.

Supplementary Table S3 reports the Pearson correlation coefficients among the variables used in the baseline regressions. The correlations between AI Capability and GreenPatents, GreenImpact, and GreenBreadth are 0.660, 0.604, and 0.614, respectively, and are statistically significant. These correlations provide preliminary evidence of positive associations between firms' AI technological capability and the quantity, impact, and knowledge breadth of green innovation. The three green innovation outcomes are also positively correlated, indicating that they capture closely related but distinct dimensions of corporate green innovation.

3.3. Model Design

To examine the effect of AI Capability on corporate green innovation, this paper estimates the following firm-year two-way fixed effects model:

$$GreenInnovation_{i,t} = \alpha + \beta AI\ Capability_{i,t-1} + \gamma Controls_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (1)$$

Table 1. Descriptive Statistics.

Variable	N	Mean	Std. Dev.	Min	Median	Max
GreenPatents	29,136	1.063	1.331	0.000	0.693	6.087
GreenImpact	29,136	0.307	0.680	0.000	0.000	4.405
GreenBreadth	29,136	4.708	9.921	0.000	1.000	90.120
AI Capability	29,136	0.814	1.293	0.000	0.000	6.361
Size	29,136	22.283	1.341	18.841	22.107	26.753
Leverage	29,136	0.448	0.188	0.047	0.450	0.888
ROA	29,136	0.043	0.049	−0.181	0.038	0.223
CashFlow	29,136	0.057	0.068	−0.188	0.054	0.288
TobinQ	29,136	1.806	1.045	0.764	1.468	9.007
FirmAge	29,136	2.856	0.388	1.099	2.890	3.714
Duality	29,136	0.222	0.416	0.000	0.000	1.000
Top10	29,136	0.579	0.153	0.217	0.584	0.917
SOE	29,136	0.473	0.499	0.000	0.000	1.000
Growth	29,136	0.154	0.319	−0.673	0.109	3.544

Notes: This table reports descriptive statistics for the baseline regression sample. Explanatory variables and controls are measured with a one-year lag. AI Capability, GreenPatents, and GreenImpact are measured as $\ln(1+x)$. Continuous variables are winsorized by year at the 1st and 99th percentiles.

In this model, i indexes firms and t indexes years. $GreenInnovation_{i,t}$ denotes corporate green innovation performance. This paper measures green innovation from three main dimensions: green innovation quantity, green innovation impact, and green knowledge breadth, corresponding to GreenPatents, GreenImpact, and GreenBreadth, respectively. The core explanatory variable, $AI\ Capability_{i,t-1}$, denotes firms' AI technological capability and is measured as the natural logarithm of one plus the number of AI patent applications. $Controls_{i,t-1}$ is a vector of firm-level control variables, as described in Section 3.2.4. Both the core explanatory variable and firm-level controls are lagged by one year to alleviate concerns that green innovation may reversely affect firms' AI technological investment. The model further includes firm fixed effects, μ_i, to absorb time-invariant firm heterogeneity, such as firms' long-term innovation capability, organizational culture, and governance foundations. It also includes year fixed effects, λ_t, to absorb year-level shocks, such as macroeconomic fluctuations, changes in the policy environment, and common technological trends. Standard errors are clustered at the firm level to allow for serial correlation within firms. The coefficient of interest is β, which captures the relationship between AI Capability and green innovation. A significantly positive β indicates that stronger AI technological capability is associated with higher levels of green innovation.

4. Empirical Results

4.1. Baseline Results

Table 2 reports the baseline regression results for the relationship between AI Capability and corporate green innovation. Columns (1)–(2), (3)–(4), and (5)–(6) present the results using green innovation quantity (GreenPatents), green innovation impact (GreenImpact), and green knowledge breadth (GreenBreadth) as dependent variables, respectively. All models include firm and year fixed effects, and standard errors are clustered at the firm level. Columns (1), (3), and (5) include only the core explanatory variable, while columns (2), (4), and (6) further add firm-level controls.

Higher lagged AI Capability is positively associated with green patent output, green innovation impact, and green knowledge breadth. In the specifications with controls, the coefficients on AI Capability are 0.384 for GreenPatents, 0.220 for GreenImpact, and 3.764 for GreenBreadth, all significant at the 1% level. The corresponding standard errors are

0.013, 0.011, and 0.216. The estimates remain positive and similar in magnitude across specifications with and without controls. In terms of economic interpretation, because AI Capability, GreenPatents, and GreenImpact are measured as $\ln(1+x)$, their coefficients describe relationships between transformed counts. For illustration, an increase in AI patent applications from zero to one raises AI Capability by $\ln 2$. Holding other regressors and fixed effects constant, this change corresponds to fitted differences of 0.266 in GreenPatents ($0.384 \times \ln 2$) and 0.152 in GreenImpact ($0.220 \times \ln 2$) on their logarithmic scales, and approximately 2.61 additional IPC classes in GreenBreadth ($3.764 \times \ln 2$).

Table 2. Patent-Based AI Capability and Corporate Green Innovation.

	GreenPatents		**GreenImpact**		**GreenBreadth**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
AI Capability	0.411 ***	0.384 ***	0.230 ***	0.220 ***	3.935 ***	3.764 ***
	(0.013)	(0.013)	(0.011)	(0.011)	(0.220)	(0.216)
Size		0.211 ***		0.086 ***		1.266 ***
		(0.023)		(0.014)		(0.240)
Leverage		−0.049		−0.068		−1.542 *
		(0.083)		(0.048)		(0.798)
ROA		0.347 **		0.067		2.501 *
		(0.170)		(0.102)		(1.494)
CashFlow		0.039		−0.023		0.161
		(0.093)		(0.053)		(0.801)
TobinQ		0.011		0.013 **		-0.055
		(0.008)		(0.005)		(0.068)
FirmAge		0.120		0.033		3.825 **
		(0.115)		(0.076)		(1.555)
Duality		0.024		−0.001		−0.078
		(0.022)		(0.014)		(0.200)
Top10		0.233 **		0.078		5.321 ***
		(0.105)		(0.059)		(1.059)
SOE		0.066		0.018		−0.308
		(0.042)		(0.026)		(0.483)
Growth		−0.012		0.000		−0.160
		(0.018)		(0.011)		(0.144)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	29,136	29,136	29,136	29,136	29,136	29,136
Adjusted R^2	0.764	0.769	0.623	0.626	0.701	0.707

Notes: This table reports firm-year regressions using one-year lagged AI Capability and one-year lagged controls. AI Capability, GreenPatents, and GreenImpact are measured as $\ln(1+x)$. All models include firm and year fixed effects. Standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Overall, the baseline findings are consistent with Hypothesis 1. Firm fixed effects account for time-invariant firm characteristics, and year fixed effects absorb common annual shocks. Nevertheless, these controls and the lagged specification do not eliminate potential time-varying confounding or reverse causality. The following robustness checks assess the sensitivity of the findings to alternative measurements, model specifications, and identification approaches.

4.2. Robustness Checks

4.2.1. Alternative Measurements

Table 3 examines whether the baseline association persists when alternative AI measures are used. Columns (1)–(3) use Any_AI, an indicator of whether the firm and its subsidiaries file at least one AI patent application in a given year. This measure captures the presence rather than the volume of AI patenting activity. Columns (4)–(6) use the MD&A-based AI measure, which is constructed by applying the 73-item AI keyword dictionary developed by Yao et al. [31] to the management discussion and analysis sections of firms' annual reports. The full dictionary is reported in Supplementary Table S2. Columns (7)–(9) use AIHiring, which applies the same dictionary to job-posting texts publicly collected from major Chinese recruitment-information platforms. AIHiring is measured as the natural logarithm of one plus the number of deduplicated AI-related job postings matched to the listed firm and its subsidiaries. Whereas the MD&A-based measure captures firms' disclosed attention to AI, AIHiring captures their recruitment demand for AI-related human capital. All three measures enter the regressions with a one-year lag. Their estimated coefficients are positive and significant at the 1% level for GreenPatents, GreenImpact, and GreenBreadth. The MD&A and recruitment measures provide evidence from sources other than patent records, reducing concerns that the baseline association depends entirely on patent-based measurement of both AI and green innovation. The AIHiring regressions contain 15,125 firm-year observations, compared with 29,136 for Any_AI and the MD&A-based measure, reflecting the more limited coverage of recruitment data. The hiring-based results therefore provide supplementary evidence within the sample for which recruitment data are available. Supplementary Table S4 reports correlations among the baseline and alternative AI measures. Supplementary Table S5 uses AI patent stocks constructed with depreciation rates of 10%, 15%, and 20%; the coefficients remain positive and significant at the 1% level across all three green innovation outcomes.

Table 3. Robustness Check: Alternative AI Measures.

	Any_AI			**MD&A-Based AI**			**AIHiring**		
	Green Patents (1)	**Green Impact (2)**	**Green Breadth (3)**	**Green Patents (4)**	**Green Impact (5)**	**Green Breadth (6)**	**Green Patents (7)**	**Green Impact (8)**	**Green Breadth (9)**
AI measure	0.358 ***	0.117 ***	1.698 ***	0.089 ***	0.072 ***	0.786 ***	0.051 ***	0.056 ***	0.812 ***
	(0.020)	(0.011)	(0.167)	(0.016)	(0.012)	(0.179)	(0.011)	(0.009)	(0.119)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,136	29,136	29,136	29,136	29,136	29,136	15,125	15,125	15,125
Adjusted R^2	0.742	0.584	0.648	0.735	0.584	0.646	0.832	0.704	0.833

Notes: This table reports robustness checks using alternative one-year-lagged AI measures. Columns (1)–(3) use Any_AI, which equals one if the firm owns at least one AI patent and zero otherwise. Columns (4)–(6) use the MD&A-based AI measure. Columns (7)–(9) use AIHiring, measured as the natural logarithm of one plus the number of deduplicated AI-related job postings matched to the listed firm and its subsidiaries. MD&A-based AI, GreenPatents, and GreenImpact are measured as $\ln(1+x)$. All models include one-year-lagged firm-level controls, firm fixed effects, and year fixed effects. Firm-clustered standard errors are reported in parentheses. *** indicates significance at the 1% level.

Supplementary Tables S6 and S7 examine alternative measures of green innovation. Table S6 uses green invention patent applications (GreenInv), granted green patents (GreenGrant), the share of green invention patents (GreenInvShare), and green knowledge diversity (KnowDiv). The coefficients on lagged AI Capability are positive and significant at the 1% level across these outcomes. Table S7 further assesses the citation-based measure of

innovation impact. Panel A restricts the two-year analysis to application cohorts through 2022 because later cohorts do not have a complete citation window. Panel B extends the window to three years, using complete cohorts through 2021, to examine whether the results are robust to a longer citation window. Across high-impact patent counts, total forward citations, and measures excluding self-citations, the coefficients remain positive and significant at the 1% level. Together, these tests indicate that the positive association persists across the alternative AI and green innovation measures examined.

4.2.2. Alternative Model Specification

The three green innovation outcomes are nonnegative count variables with substantial concentrations at zero and right-skewed distributions. To examine whether the baseline findings depend on the $\ln(1 + x)$ transformation or a linear conditional-mean specification, Table 4 re-estimates the models using Poisson pseudo-maximum likelihood (PPML) and the untransformed outcome counts. PPML accommodates zero-valued outcomes without adding a constant and does not require equality between the conditional mean and variance. The specifications retain the one-year-lagged AI Capability and controls, firm and year fixed effects, and firm-clustered standard errors used in the baseline analysis. The coefficients on AI Capability are 0.338 for GreenPatents, 0.358 for GreenImpact, and 0.166 for GreenBreadth, all significant at the 1% level. The smaller estimation samples result from singleton or separated observations dropped by the high-dimensional fixed-effects PPML estimator. Overall, the PPML estimates alleviate concerns that the baseline association is driven by the logarithmic transformation of the outcomes, their concentration at zero, or the linear functional-form assumption.

Table 4. Alternative Model Specification: PPML Estimates.

	GreenPatents (1)	**GreenImpact (2)**	**GreenBreadth (3)**
AI Capability	0.338 ***	0.358 ***	0.166 ***
	(0.053)	(0.077)	(0.017)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	26,342	20,051	26,342
Converged	Yes	Yes	Yes

Notes: PPML models use the underlying untransformed counts corresponding to GreenPatents, GreenImpact, and GreenBreadth. The smaller estimation samples result from singleton or separated observations dropped by the high-dimensional fixed-effects PPML estimator. Firm-clustered standard errors are reported in parentheses. *** indicates significance at the 1% level.

4.2.3. Excluding Overlapping AI and Green Patents

Because AI Capability and the green innovation outcomes are both constructed from patent data, some patent applications may satisfy both the AI and green classification criteria, potentially generating a mechanical association between the two measures. Supplementary Table S8 identifies 125,801 overlapping applications, representing 13.89% of AI patents and 25.63% of green patents; all have identical application years in the two patent datasets. Although the baseline specification uses $AI\ Capability_{t-1}$ to explain $GreenInnovation_t$, preventing the same application from directly entering both sides of the same firm-year regression observation, we conduct a more conservative test by removing all overlapping applications from the green patent set. We then reconstruct GreenPatents, GreenImpact, and GreenBreadth, including recalculation of the citation counts and application-year thresholds used to identify high-impact patents. As shown in Table 5, the coefficients on AI

Capability remain positive and significant at the 1% level, at 0.266, 0.130, and 2.131, respectively. Although these estimates are smaller than their baseline counterparts, the results indicate that the positive association is not generated solely by the dual classification of the same patents.

Table 5. Baseline Estimates after Excluding AI–Green Overlapping Patents.

	GreenPatents (1)	**GreenImpact (2)**	**GreenBreadth (3)**
AI Capability	0.266 ***	0.130 ***	2.131 ***
	(0.014)	(0.010)	(0.154)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	29,136	29,136	29,136
Adjusted R^2	0.708	0.560	0.652

Notes: Columns (1)–(3) use GreenPatentsExcl, GreenImpactExcl, and GreenBreadthExcl, respectively, reconstructed after excluding patents classified as both AI and green. Firm-clustered standard errors are reported in parentheses. *** indicates significance at the 1% level.

4.2.4. Instrumental Variable Regression

Although the baseline models use lagged AI Capability and control for firm fixed effects, year fixed effects, and firm characteristics, the estimates may still be affected by reverse causality and time-varying omitted factors. To alleviate these concerns, we construct a Bartik IV following Bartik [39] and the shift-share IV literature [40,41], interacting an industry's average AI exposure over 2001–2012 with the annual national AI technology wave. To strengthen the plausibility of the exclusion restriction, the national wave excludes firms in the focal firm's industry and province, reducing the likelihood that the instrument captures same-industry technological developments or common local shocks that may directly affect green innovation. Identification requires that, conditional on fixed effects, firm characteristics, and relevant trends, the instrument affects green innovation primarily through firm AI Capability. We further control for regional shocks and industry trends and use alternative clustering structures to assess the sensitivity of the results to this identifying assumption.

Table 6 reports the IV estimates. In the first stage, the coefficient on the Bartik IV is 1.258 and significant at the 1% level. The first-stage partial R^2 is 0.071, and the Kleibergen–Paap weak-IV F statistic is 180.597, well above conventional thresholds. The Kleibergen–Paap LM statistic is 122.723 and rejects the null of underidentification, indicating that the instrument significantly predicts AI Capability. In the second stage, the estimated coefficients of AI Capability on GreenPatents, GreenImpact, and GreenBreadth are 0.405, 0.301, and 3.120, respectively, all significant at the 1% level. The Anderson–Rubin tests reject the null of no effect for all three outcomes, indicating that the main results are not driven by weak-instrument inference.

Supplementary Table S9 reports sensitivity analyses. The coefficients remain positive and statistically significant after including province-by-year fixed effects, city-by-year fixed effects, industry-specific linear trends, and the combination of province-by-year fixed effects and industry trends. Under the more stringent two-way clustering by firm and industry, the coefficient magnitudes and directions remain stable. Although the standard errors increase, all three estimates remain significant at least at the 5% level. Overall, the Bartik IV estimates and sensitivity analyses provide further support for the baseline findings. Because this evidence remains conditional on the exclusion restriction, we interpret it

as complementary identification evidence for the positive relationship between firm AI Capability and green innovation.

Table 6. Instrumental-Variable Results Using the Bartik IV.

	GreenPatents (1)	GreenImpact (2)	GreenBreadth (3)
Panel A: First-stage results for AI Capability			
Bartik IV		1.258 ***	
		(0.094)	
First-stage partial R^2		0.071	
KP weak-IV *F*		180.597	
KP LM		122.723	
Panel B: Second-stage results			
AI Capability	0.405 ***	0.301 ***	3.120 ***
	(0.046)	(0.032)	(0.581)
Anderson–Rubin *p*-value	<0.001	<0.001	<0.001
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	26,427	26,427	26,427

Notes: This table reports two-stage least-squares estimates using the Bartik instrument for one-year-lagged *AI Capability*. The instrument interacts an industry's average AI exposure over 2001–2012 with an external national AI wave constructed from firms outside the focal firm's industry and province. The Kleibergen–Paap LM statistic tests underidentification, and the Kleibergen–Paap weak-IV *F*-statistic assesses first-stage strength under firm-clustered inference. The Anderson–Rubin test evaluates the null of a zero structural coefficient using weak-identification-robust inference. All models include one-year-lagged controls, firm fixed effects, and year fixed effects. Firm-clustered standard errors are reported in parentheses. Italicized text identifies panel headings. *** indicates significance at the 1% level.

4.2.5. AI Innovation and Development Pilot Zones as a Policy Shock

To further alleviate concerns about reverse causality and omitted variables, we exploit the staggered establishment of the National New Generation Artificial Intelligence Innovation and Development Pilot Zones (AIIDPZ). A firm enters the treated cohort in the calendar year in which its recorded city is approved as a pilot zone ($t = 0$), while firms in never-treated cities form the control group. The policy covers three cohorts approved in 2019, 2020, and 2021. Supplementary Table S10 reports the official pilot units, matched cities, and firms represented in each cohort. Because treatment timing differs across cities and policy effects may be heterogeneous, we use the Sun–Abraham interaction-weighted estimator with firm and year fixed effects, firm-level controls, and firm-clustered standard errors.

Table 7 reports the average Sun–Abraham DID effects. Column (1) first examines whether AIIDPZ effectively improves the AI Capability of firms located in pilot zones, while columns (2)–(4) further examine the responses of corporate green innovation to the policy. The Pre avg estimates are statistically insignificant across all four outcomes. More importantly, the formal joint tests reported in Supplementary Table S11 fail to reject that the four pre-treatment coefficients are jointly zero, with *p*-values of 0.622 for AI Capability, 0.611 for GreenPatents, 0.688 for GreenImpact, and 0.263 for GreenBreadth, suggesting no significant pre-treatment trend differences between treated and control firms. The Post avg and ATT estimates are both significantly positive. Specifically, AIIDPZ significantly increases firms' AI Capability and also raises GreenPatents, GreenImpact, and GreenBreadth. These results indicate that AIIDPZ not only strengthens firms' AI technological capability but also improves the quantity, impact, and knowledge breadth of corporate green innovation.

Table 7. Policy-Shock Evidence: Sun–Abraham Average Effects.

	AI Capability (1)	GreenPatents (2)	GreenImpact (3)	GreenBreadth (4)
Pre avg	0.018	0.043	0.011	−0.114
	(0.026)	(0.032)	(0.014)	(0.164)
Post avg	0.079 ***	0.069 **	0.039 **	0.411 **
	(0.026)	(0.032)	(0.016)	(0.181)
ATT	0.068 ***	0.070 **	0.034 **	0.415 **
	(0.026)	(0.033)	(0.015)	(0.183)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Control group	Never-treated	Never-treated	Never-treated	Never-treated
Observations	32,412	32,412	32,412	32,412

Notes: This table reports Sun–Abraham interaction-weighted staggered DID estimates for the AI pilot policy. Pre avg is the equal-weight average of the coefficients from $t \leq -5$ to $t = -2$, while Post avg averages $t = 0$ through $t = 4$. ATT aggregates all available post-treatment cohort-by-event-time effects using their shares of treated post-treatment firm-year observations. The omitted event time is $t = -1$. The policy-shock analysis defines treatment by the contemporaneous policy status, so its sample size differs from the lagged baseline regressions. All models include firm and year fixed effects and firm-level controls. Standard errors are clustered at the firm level. *** and ** indicate significance at the 1% and 5% levels, respectively.

Figure 1 and Supplementary Table S11 show the dynamic estimates. AI Capability increases significantly in the treatment year and remains positive and significant through $t = 4$. The green innovation responses are less immediate and less uniform: GreenPatents and GreenImpact are not statistically significant in the treatment year, while all three green innovation outcomes are significantly positive at $t = 2$. This temporal pattern is consistent with firms' AI Capability responding before the green innovation outcomes become more pronounced. Moreover, because the later event periods are supported by fewer treatment cohorts, the estimates provide stronger evidence on short- and medium-term responses than on persistent long-run effects. Finally, since pilot-zone designation may not be random, unobserved time-varying differences between pilot and non-pilot cities cannot be fully excluded. We therefore interpret these estimates as complementary policy-shock evidence.

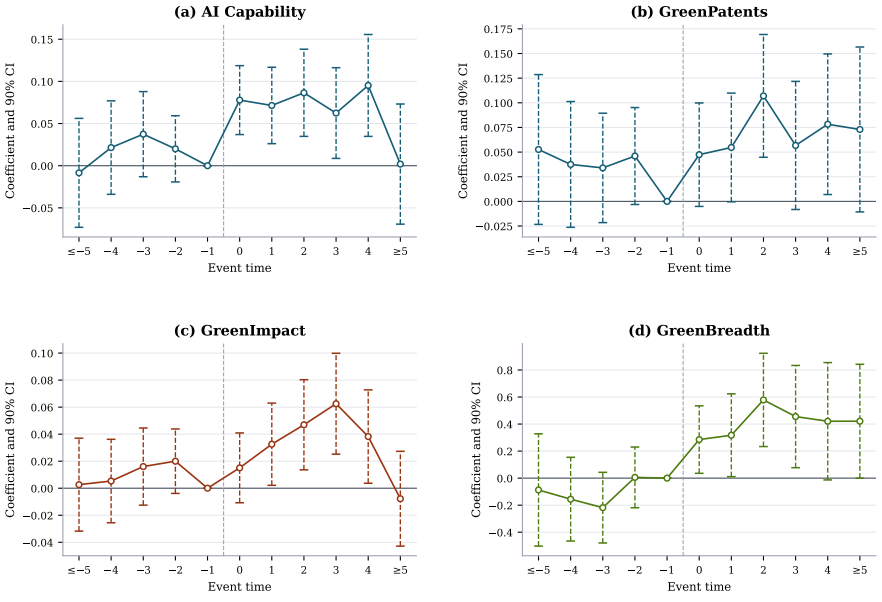


Figure 1. Dynamic Effects of the AI Pilot Policy on AI Capability and Green Innovation. Notes: Colored lines and markers show event-time estimates, dashed error bars denote 90% confidence intervals, and the gray vertical dashed line separates the pre- and post-treatment periods.

4.2.6. Other Robustness Tests

Supplementary Table S12 examines whether the results for GreenImpact and GreenBreadth are absorbed by firms' pre-existing green patent volume. After adding one-year-lagged GreenPatents to the corresponding baseline specifications, the coefficients on AI Capability remain positive and significant at the 1% level, at 0.125 for GreenImpact and 2.279 for GreenBreadth, indicating that the results are not driven solely by prior green-patent scale.

Supplementary Tables S13 and S14 assess sensitivity to observed and unobserved heterogeneity. Table S13 shows that the coefficients remain positive and significant after introducing industry-by-year, province-by-year, and city-by-year fixed effects and firm-specific linear trends. The Oster test reported in Table S14 produces delta values of 3.439, 3.814, and 1.888 for GreenPatents, GreenImpact, and GreenBreadth, respectively, suggesting that selection on unobservables would need to be stronger than selection on observables to explain away the baseline estimates.

Finally, Supplementary Table S15 applies alternative one-way clustering by firm, city, industry, and province, as well as two-way clustering by firm and year and by firm and city. The coefficient estimates remain unchanged and statistically significant at the 1% level. Collectively, these tests show that the findings are robust to pre-existing green patent volume, alternative fixed-effect structures, coefficient-stability assumptions, and clustering choices.

5. Mechanism Analysis

The preceding analyses document a robust positive association between AI Capability and corporate green innovation. This section examines two theoretically motivated channels: knowledge fusion and technology cooperation. We employ a strict-timing design, $AI\ Capability_{t-2} \rightarrow Mechanism_{t-1} \rightarrow Green\ Innovation_t$, to reduce concerns about contemporaneous correlation and reverse causality.

5.1. Knowledge Fusion Channel

Table 8 examines the knowledge-fusion channel using the strict-timing sequence $AI\ Capability_{t-2} \rightarrow Knowledge\ Fusion_{t-1} \rightarrow Green\ Innovation_t$. The baseline measure, KnowFusion, counts the overlapping four-character IPC classes in a firm's AI and green patent portfolios. We use this measure as the baseline because it provides a transparent and intuitive indicator of the technological overlap between the two patent portfolios. However, the overlap count may increase mechanically with the sizes of the two portfolios. We therefore also use three normalized measures. The Jaccard index scales the overlap by the union of the two IPC sets, Binary Cosine scales it by the geometric mean of their sizes, and the Excess Overlap Z-score evaluates observed overlap relative to its expected level given the two set sizes and the available IPC-class universe. These measures capture technological proximity and co-occurrence between firms' AI and green knowledge bases.

Table 8. Strict-Timing Knowledge-Fusion Mechanism Tests.

	Step 2	**Steps 1 and 3**		
	Fusion Measure	**Green Patents**	**Green Impact**	**Green Breadth**
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Step 1 total effects				
AI Capability		0.327 ***	0.191 ***	3.546 ***
		(0.013)	(0.011)	(0.225)
Adjusted R^2		0.767	0.624	0.706

Table 8. *Cont.*

	Step 2	Steps 1 and 3		
	Fusion Measure (1)	**Green Patents (2)**	**Green Impact (3)**	**Green Breadth (4)**
Panel B: KnowFusion (Overlap)				
AI Capability	1.952 ***	0.264 ***	0.126 ***	1.586 ***
	(0.139)	(0.012)	(0.010)	(0.129)
KnowFusion (Overlap)		0.033 ***	0.033 ***	1.004 ***
		(0.004)	(0.003)	(0.049)
Adjusted R^2	0.626	0.771	0.642	0.784
Indirect effect ($a \times b$)		0.064	0.065	1.960
Mediation ratio		19.43%	34.01%	55.27%
Sobel Z		7.423 ***	8.878 ***	11.574 ***
Bootstrap 95% CI		[0.053, 0.076]	[0.054, 0.076]	[1.668, 2.261]
Panel C: Jaccard				
AI Capability	0.036 ***	0.319 ***	0.186 ***	3.508 ***
	(0.002)	(0.013)	(0.011)	(0.221)
Jaccard		0.232 ***	0.157 ***	1.030 ***
		(0.033)	(0.022)	(0.266)
Adjusted R^2	0.353	0.767	0.625	0.706
Indirect effect ($a \times b$)		0.008	0.006	0.037
Mediation ratio		2.57%	2.98%	1.05%
Sobel Z		6.485 ***	6.564 ***	3.772 ***
Bootstrap 95% CI		[0.006, 0.011]	[0.004, 0.008]	[0.021, 0.055]
Panel D: Binary Cosine				
AI Capability	0.057 ***	0.310 ***	0.181 ***	3.455 ***
	(0.003)	(0.013)	(0.011)	(0.219)
Binary Cosine		0.304 ***	0.173 ***	1.597 ***
		(0.028)	(0.019)	(0.241)
Adjusted R^2	0.436	0.768	0.625	0.707
Indirect effect ($a \times b$)		0.017	0.010	0.091
Mediation ratio		5.28%	5.14%	2.56%
Sobel Z		9.597 ***	8.345 ***	6.336 ***
Bootstrap 95% CI		[0.014, 0.021]	[0.007, 0.012]	[0.067, 0.118]
Panel E: Excess Overlap Z-score				
AI Capability	1.264 ***	0.311 ***	0.182 ***	3.467 ***
	(0.057)	(0.013)	(0.011)	(0.220)
Excess Overlap Z-score		0.013 ***	0.008 ***	0.062 ***
		(0.001)	(0.001)	(0.011)
Adjusted R^2	0.432	0.768	0.625	0.707
Indirect effect ($a \times b$)		0.016	0.010	0.079
Mediation ratio		4.93%	4.98%	2.23%
Sobel Z		9.188 ***	8.172 ***	5.739 ***
Bootstrap 95% CI		[0.013, 0.020]	[0.007, 0.012]	[0.056, 0.105]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	26,662	26,662	26,662	26,662

Notes: Panel A reports Step 1, which regresses each green innovation outcome in year t on *AI Capability* in year $t-2$. In Panels B–E, column (1) reports Step 2 and columns (2)–(4) report Step 3. The indirect effect is $a \times b$, and the mediation ratio is $(a \times b)/c$, where c is the corresponding Step 1 total effect. *KnowFusion (Overlap)* is the number of overlapping IPC four-character classes in a firm's AI and green patents; the other three measures normalize this overlap for the sizes of the underlying IPC sets. All models include controls measured in year $t-2$, firm fixed effects, and year fixed effects. Firm-clustered standard errors are reported in parentheses. Bootstrap rows report percentile 95% confidence intervals for the indirect effects based on 1000 firm-cluster resamples; each resample re-estimates both paths a and b. Italicized text identifies panel headings. *** indicates significance at the 1% level.

Panel A shows that $AI\ Capability_{t-2}$ is positively associated with all three green innovation outcomes at t, with all coefficients significant at the 1% level. Panels B–E further show that higher AI Capability predicts greater knowledge fusion in the following year. In the Step 3 regressions, the knowledge-fusion measures and AI Capability are both positively associated with the three green innovation outcomes at the 1% significance level, while the coefficients on AI Capability are smaller than the corresponding total-effect estimates in Panel A. This pattern is consistent with knowledge fusion serving as a potential channel underlying the baseline relationship.

The estimated indirect effects are positive across all four measures and all three outcomes. The Sobel tests reject a zero indirect effect, and the percentile 95% confidence intervals from 1000 firm-cluster bootstrap resamples exclude zero in every specification. The mediation ratios based on the raw overlap count range from 19.43% to 55.27%, whereas those based on the normalized measures range from 1.05% to 5.28%. The estimated magnitude is therefore sensitive to how knowledge fusion is measured, but the direction of the evidence is consistent across measures. Overall, the results provide evidence consistent with Hypothesis 2, while the patent-based measures capture technological overlap rather than directly observed knowledge integration within firms.

5.2. Technology Cooperation Channel

Table 9 examines the technology-cooperation channel using the strict-timing sequence $AI\ Capability_{t-2} \rightarrow Technology\ Cooperation_{t-1} \rightarrow Green\ Innovation_t$. TechCoop is measured as the natural logarithm of one plus the number of distinct external partners in a firm's green patent co-applications. To identify external rather than intra-group cooperation, we remove from the co-applicant list any name that can be matched to the focal listed firm or one of its subsidiaries in the same firm-year. We further distinguish between external firm partners (FirmCoop) and university or research-institution partners (UnivCoop) to examine which types of cooperative relationships drive the technology cooperation mechanism. The hierarchical classification procedure gives priority to corporate legal-form indicators when organization names contain both corporate and research-related terms, reducing the misclassification of corporate research institutes as universities or independent research institutions.

Panel A reports positive total-effect estimates for all three green innovation outcomes, significant at the 1% level. Panels B–D show that higher $AI\ Capability_{t-2}$ predicts greater overall, inter-firm, and university/research cooperation at $t-1$. In the Step 3 regressions, each cooperation measure and AI Capability is positively associated with GreenPatents, GreenImpact, and GreenBreadth at the 1% significance level, while the coefficients on AI Capability are smaller than the corresponding total-effect estimates. The estimated indirect effects are positive in all specifications. The Sobel tests reject zero indirect effects, and the percentile 95% confidence intervals from 1000 firm-cluster bootstrap resamples exclude zero. The mediation ratios range from 15.82% to 22.38% for overall cooperation, from 14.52% to 21.47% for inter-firm cooperation, and from 6.05% to 13.86% for university/research cooperation. Overall, the results in Table 9 are consistent with Hypothesis 3.

Table 10 examines whether the results depend on the number of distinct external partners by considering three alternative definitions. CoopIntensity captures the number of green patent applications involving at least one external partner, RepeatCoop counts current partners observed in any earlier year, and ContinuingCoop counts current partners also observed in the immediately preceding year.

Table 9. Strictly Timed Three-Step Tests of the Technology-Cooperation Mechanism.

	Step 2	Steps 1 and 3		
	Mechanism Variable (1)	**Green Patents (2)**	**Green Impact (3)**	**Green Breadth (4)**
Panel A: Step 1 total effects				
AI Capability		0.324 ***	0.190 ***	3.480 ***
		(0.013)	(0.011)	(0.224)
Adjusted R^2		0.766	0.623	0.707
Panel B: Overall technology cooperation				
AI Capability	0.155 ***	0.273 ***	0.157 ***	2.701 ***
	(0.012)	(0.012)	(0.010)	(0.166)
TechCoop		0.331 ***	0.212 ***	5.033 ***
		(0.019)	(0.015)	(0.310)
Adjusted R^2	0.631	0.775	0.637	0.745
Indirect effect ($a \times b$)		0.051	0.033	0.779
Mediation ratio		15.82%	17.33%	22.38%
Sobel Z		10.475 ***	9.529 ***	10.123 ***
Bootstrap 95% CI		[0.041, 0.061]	[0.025, 0.041]	[0.604, 0.969]
Panel C: Inter-firm technology cooperation				
AI Capability	0.142 ***	0.277 ***	0.159 ***	2.733 ***
	(0.012)	(0.013)	(0.010)	(0.165)
FirmCoop		0.333 ***	0.220 ***	5.277 ***
		(0.020)	(0.016)	(0.337)
Adjusted R^2	0.620	0.774	0.636	0.744
Indirect effect ($a \times b$)		0.047	0.031	0.747
Mediation ratio		14.52%	16.39%	21.47%
Sobel Z		9.726 ***	8.960 ***	9.498 ***
Bootstrap 95% CI		[0.037, 0.058]	[0.023, 0.040]	[0.569, 0.946]
Panel D: University/research technology cooperation				
AI Capability	0.059 ***	0.305 ***	0.174 ***	2.998 ***
	(0.006)	(0.013)	(0.011)	(0.185)
UnivCoop		0.334 ***	0.273 ***	8.220 ***
		(0.031)	(0.028)	(0.571)
Adjusted R^2	0.473	0.768	0.629	0.735
Indirect effect ($a \times b$)		0.020	0.016	0.482
Mediation ratio		6.05%	8.45%	13.86%
Sobel Z		7.049 ***	6.765 ***	7.823 ***
Bootstrap 95% CI		[0.014, 0.025]	[0.011, 0.022]	[0.349, 0.638]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	26,026	26,026	26,026	26,026

Notes: Panel A reports Step 1, which regresses each green innovation outcome in year t on *AI Capability* in year $t-2$. In Panels B–D, column (1) reports Step 2 and columns (2)–(4) report Step 3. The indirect effect is $a \times b$, and the mediation ratio is $(a \times b)/c$, where c is the corresponding Step 1 total effect. *TechCoop*, *FirmCoop*, and *UnivCoop* are $\ln(1+x)$, where x is the number of corresponding external partners in green patent co-applications. Before these variables are constructed, all listed-firm and subsidiary names identifiable under the same stock code and year are excluded from the set of co-applicants. Firm and university/research partners are identified using the hierarchical entity-classification procedure described in the text. All models include controls measured in year $t-2$, firm fixed effects, and year fixed effects. Firm-clustered standard errors are reported in parentheses. Bootstrap rows report percentile 95% confidence intervals for the indirect effects based on 1000 firm-cluster resamples; each resample re-estimates both paths a and b. Italicized text identifies panel headings. *** indicates significance at the 1% level.

Table 10. Alternative Definitions of the Technology-Cooperation Mechanism.

	Step 2	Step 3		
	Mechanism Variable (1)	**Green Patents (2)**	**Green Impact (3)**	**Green Breadth (4)**
Panel A: Cooperative green-patent activity intensity				
AI Capability	0.196 ***	0.267 ***	0.153 ***	2.630 ***
	(0.015)	(0.012)	(0.010)	(0.163)
CoopIntensity		0.293 ***	0.188 ***	4.333 ***
		(0.015)	(0.012)	(0.263)
Adjusted R^2	0.654	0.776	0.639	0.748
Indirect effect ($a \times b$)		0.057	0.037	0.850
Mediation ratio		17.72%	19.41%	24.44%
Sobel Z		10.673 ***	9.788 ***	10.149 ***
Bootstrap 95% CI		[0.046, 0.069]	[0.028, 0.046]	[0.661, 1.063]
Panel B: Repeated technology-cooperation partners				
AI Capability	0.110 ***	0.289 ***	0.163 ***	2.713 ***
	(0.011)	(0.013)	(0.010)	(0.164)
RepeatCoop		0.318 ***	0.244 ***	6.984 ***
		(0.026)	(0.023)	(0.483)
Adjusted R^2	0.615	0.770	0.632	0.743
Indirect effect ($a \times b$)		0.035	0.027	0.767
Mediation ratio		10.76%	14.12%	22.05%
Sobel Z		7.813 ***	7.410 ***	8.364 ***
Bootstrap 95% CI		[0.026, 0.044]	[0.019, 0.035]	[0.549, 0.998]
Panel C: Consecutive-year technology-cooperation partners				
AI Capability	0.097 ***	0.293 ***	0.165 ***	2.752 ***
	(0.010)	(0.013)	(0.011)	(0.174)
ContinuingCoop		0.319 ***	0.255 ***	7.485 ***
		(0.028)	(0.024)	(0.533)
Adjusted R^2	0.582	0.769	0.631	0.741
Indirect effect ($a \times b$)		0.031	0.025	0.728
Mediation ratio		9.57%	13.08%	20.93%
Sobel Z		7.367 ***	7.180 ***	8.006 ***
Bootstrap 95% CI		[0.023, 0.039]	[0.017, 0.033]	[0.521, 0.957]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	26,026	26,026	26,026	26,026

Notes: Column (1) reports Step 2 and columns (2)–(4) report Step 3 under the sequence $AI\ Capability_{t-2} \rightarrow Technology\ Cooperation_{t-1} \rightarrow Green\ Innovation_t$. The Step 1 total effects are reported in Panel A of Table 9 and equal 0.324, 0.190, and 3.480 across the three outcomes. Before each measure is constructed, all listed-firm and subsidiary names identifiable under the same stock code and year are excluded. *CoopIntensity* is $\ln(1+x)$, where x is the number of green patents with at least one remaining external co-applicant. *RepeatCoop* is $\ln(1+x)$, where x is the number of current external partners observed in any earlier year. *ContinuingCoop* is $\ln(1+x)$, where x is the number of current external partners also observed in the immediately preceding year. All models include controls measured in year $t-2$, firm fixed effects, and year fixed effects. Firm-clustered standard errors are reported in parentheses. Bootstrap rows report percentile 95% confidence intervals for the indirect effects based on 1000 firm-cluster resamples; each resample re-estimates both paths a and b. Italicized text identifies panel headings. *** indicates significance at the 1% level.

Across all three measures, AI Capability positively predicts subsequent cooperation, and the cooperation measures are positively associated with the three green innovation outcomes at the 1% level. All bootstrap confidence intervals for the indirect effects exclude

zero, with mediation ratios ranging from 9.57% to 24.44%. The consistent results across cooperation breadth, activity intensity, and persistent partnership measures provide further evidence consistent with the proposed technology-cooperation channel.

6. Heterogeneity Analysis

To examine the boundary conditions of the relationship between AI Capability and corporate green innovation, we organize the heterogeneity analysis around three contextual conditions that may shape firms' ability and incentives to translate AI technological capability into green innovation: organizational resources and policy orientation, green transition pressure, and urban digital infrastructure. Ownership status distinguishes firms with different access to resources, policy responsiveness, and market incentives; heavy-polluting-industry status reflects differences in environmental regulation and transition pressure; and urban internet penetration represents the external digital environment supporting information flows and AI application.

6.1. Ownership: SOEs Versus Non-SOEs

Ownership may condition the relationship between AI Capability and green innovation through differences in resource access, policy orientation, and market incentives. SOEs generally have greater access to financing, research infrastructure, and policy-supported innovation resources, and they may be more responsive to national digitalization and green-transition objectives. These advantages can facilitate the complementary investments and long-term R&D required to translate AI technological capability into green innovation. However, non-SOEs may partly offset their resource disadvantages through stronger competitive incentives, greater organizational flexibility, and faster responses to market opportunities. The direction of ownership heterogeneity is therefore not unambiguous. To examine this issue, we interact AI Capability with SOE, which equals one for state-owned enterprises and zero for non-SOEs.

Panel A of Table 11 reports the conditional associations by ownership type and formally tests the differences between them. Among non-SOEs, the coefficients on AI Capability are 0.285 for GreenPatents, 0.157 for GreenImpact, and 2.340 for GreenBreadth, all significant at the 1% level. The corresponding coefficients among SOEs are 0.466, 0.272, and 4.952, respectively, and are also significant at the 1% level. The SOE–non-SOE differences are 0.181, 0.116, and 2.611, all statistically significant at the 1% level. Thus, AI Capability is positively associated with all three dimensions of green innovation in both ownership groups, but the associations are significantly stronger among SOEs. This pattern is consistent with greater resource access and stronger policy responsiveness facilitating the translation of AI technological capability into green innovation, while the positive estimates among non-SOEs suggest that market incentives and organizational flexibility may also support this relationship.

6.2. Green Transition Pressure: Heavy-Polluting Industries

Industry-level green transition pressure may condition the relationship between AI Capability and green innovation. Firms in heavy-polluting industries face stronger environmental regulation, emission-reduction requirements, and compliance costs, which can increase their incentives to apply AI to production optimization, energy-efficiency management, pollution monitoring, and green technology R&D. These pressures may encourage firms to expand green innovation activities and apply AI across a broader range of technological fields. However, the association need not be stronger for every dimension of green innovation, since compliance-oriented or application-specific innovations may not necessarily generate greater subsequent technological impact. We therefore use Pollute,

which equals one for firms in heavy-polluting industries and zero otherwise, to examine whether the relationship between AI Capability and green innovation differs with industry-level transition pressure.

Table 11. Heterogeneity Analysis: Conditional and Marginal Effects.

	GreenPatents (1)	GreenImpact (2)	GreenBreadth (3)
Panel A: Ownership			
AI effect: Non-SOEs	0.285 ***	0.157 ***	2.340 ***
	(0.016)	(0.013)	(0.251)
AI effect: SOEs	0.466 ***	0.272 ***	4.952 ***
	(0.016)	(0.014)	(0.302)
Difference: SOEs minus Non-SOEs	0.181 ***	0.116 ***	2.611 ***
	(0.020)	(0.018)	(0.386)
Observations	29,136	29,136	29,136
Adjusted R^2	0.772	0.630	0.718
Panel B: Pollution intensity			
AI effect: Non-polluting firms	0.367 ***	0.222 ***	3.376 ***
	(0.014)	(0.012)	(0.234)
AI effect: Polluting firms	0.446 ***	0.212 ***	5.183 ***
	(0.026)	(0.021)	(0.480)
Difference: Polluting minus Non-polluting	0.080 ***	−0.010	1.807 ***
	(0.029)	(0.024)	(0.533)
Observations	29,136	29,136	29,136
Adjusted R^2	0.769	0.626	0.710
Panel C: Urban internet penetration			
AI marginal effect at Internet P25	0.357 ***	0.177 ***	1.998 ***
	(0.016)	(0.013)	(0.206)
AI marginal effect at Internet mean	0.362 ***	0.200 ***	3.006 ***
	(0.014)	(0.011)	(0.196)
AI marginal effect at Internet P75	0.367 ***	0.225 ***	4.075 ***
	(0.013)	(0.011)	(0.240)
Difference: P75 minus P25	0.010	0.048 ***	2.077 ***
	(0.011)	(0.010)	(0.213)
Observations	24,539	24,539	24,539
Adjusted R^2	0.780	0.646	0.732
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Panels A and B report linear combinations from the corresponding interaction models. The first two rows of each panel are the conditional effects of *AI Capability* in the two groups, and the difference row tests whether these effects differ. Panel C reports the marginal effect of *AI Capability* at the 25th percentile (20.627), sample mean (31.489), and 75th percentile (42.996) of urban internet penetration. Its difference row compares the marginal effects at P75 and P25. *AI Capability* and firm-level controls are lagged by one year. All models include firm and year fixed effects. Firm-clustered standard errors are reported in parentheses. Italicized text identifies panel headings. *** indicates significance at the 1% level.

Panel B of Table 11 reports the conditional associations for the two groups and formally tests their differences. Among non-heavy-polluting firms, the coefficients on AI Capability are 0.367 for GreenPatents, 0.222 for GreenImpact, and 3.376 for GreenBreadth, all significant at the 1% level. The corresponding coefficients among heavy-polluting firms are 0.446, 0.212, and 5.183, respectively, and are also significant at the 1% level. The differences between heavy-polluting and non-heavy-polluting firms are 0.080 for GreenPatents and 1.807

for GreenBreadth, both positive and significant at the 1% level. By contrast, the difference for GreenImpact is −0.010 and statistically insignificant. These results indicate that AI Capability is positively associated with all three green innovation outcomes in both groups. The stronger associations for GreenPatents and GreenBreadth among heavy-polluting firms are consistent with green transition pressure encouraging broader AI-supported green innovation activities, whereas the results do not support a stronger association with green innovation impact.

6.3. Urban Digital Infrastructure: Internet Penetration

Urban digital infrastructure may condition the relationship between AI Capability and green innovation by supporting data circulation, information access, digital collaboration, and the application of AI technologies. Firms located in cities with higher internet penetration may be better able to access external technological information, coordinate digital R&D activities, and apply AI to the search and recombination of green knowledge. Different dimensions of green innovation may respond differently to this digital environment, making it useful to examine green innovation output, technological impact, and knowledge breadth separately. Following Zhao et al. [42], we use prefecture-level internet penetration to measure the urban digital environment and interact this continuous variable with AI Capability. We evaluate the marginal association of AI Capability at the 25th percentile, sample mean, and 75th percentile of internet penetration, corresponding to 20.627, 31.489, and 42.996, respectively.

Panel C of Table 11 reports the results. At the 25th percentile, mean, and 75th percentile of internet penetration, the marginal associations between AI Capability and GreenPatents are 0.357, 0.362, and 0.367; those for GreenImpact are 0.177, 0.200, and 0.225; and those for GreenBreadth are 1.998, 3.006, and 4.075, respectively. All these estimates are positive and significant at the 1% level. The P75–P25 differences are 0.048 for GreenImpact and 2.077 for GreenBreadth, both positive and significant at the 1% level. By contrast, the corresponding difference for GreenPatents is 0.010 and statistically insignificant. Thus, the positive association of AI Capability with green innovation is observed throughout the reported range of internet penetration. Higher urban internet penetration is associated with stronger relationships for green innovation impact and knowledge breadth, whereas the evidence does not indicate a statistically significant difference for green patent output. Supplementary Figure S1 presents the marginal associations and confidence intervals over the observed range of internet penetration.

7. Conclusions

Using a firm-year panel of Chinese A-share firms listed on the Shanghai and Shenzhen main boards from 2002 to 2024, this paper examines the relationship between firms' patent-based AI capability and green innovation and the potential channels underlying this relationship. The baseline estimates show that higher lagged AI Capability is positively associated with green patent output, citation-based impact, and green technological breadth. Using a strict temporal sequence and formal indirect-effect tests, the mechanism analyses provide evidence consistent with knowledge fusion and technology cooperation as two potential channels underlying this relationship. These patterns remain consistent across normalized knowledge-overlap measures and alternative measures of formal cooperation. Overall, the findings document a positive relationship between patent-based AI technological accumulation and multiple dimensions of corporate green innovation, together with evidence consistent with the proposed roles of knowledge fusion and formal technology cooperation.

These findings can be understood in the broader context of how AI reshapes firms' green technological change. Existing studies emphasize AI as a digital technology that improves prediction, information processing, resource allocation, and corporate governance [2,3,7,10]. Building on this perspective, our study shifts attention to the innovation process by documenting observable relationships between AI capability, technological knowledge overlap, and formal cross-organizational collaboration. Specifically, firms with stronger AI capability subsequently exhibit greater overlap between their AI and green patent portfolios and broader formal cooperation with external partners. These potential roles may be particularly relevant to green innovation, which often involves complex knowledge combinations across energy, materials, production processes, pollution control, and digital technologies [12,13]. A central challenge in green innovation is therefore to recombine heterogeneous knowledge and coordinate cross-organizational innovation, in addition to increasing R&D input. The positive relationships between AI capability and both green innovation impact and green knowledge breadth further suggest that AI capability is associated not only with more green patent applications, but also with outcomes characterized by greater citation-based impact and broader technological coverage. Accordingly, the findings are consistent with a broader view that extends the role of AI in green innovation from efficiency improvements associated with digital technology investment to technological search, knowledge recombination, and collaborative development.

The findings also have policy and managerial implications. First, AI pilot-zone and digital-infrastructure policies could be coordinated more closely with support for green R&D in areas such as energy conservation, pollution control, and low-carbon production. For example, policymakers could explore coordinating these initiatives with green credit, carbon-market-related innovation incentives, and public R&D funding, while evaluating their effectiveness before wider implementation. Second, evaluations of green innovation policies and funding programs could supplement patent counts with measures of citation-based impact and technological breadth. Where data are available, these indicators could also be considered alongside actual energy-use and emissions outcomes. Finally, firms could integrate AI capability into green R&D and innovation management by connecting AI and environmental R&D teams and facilitating formal collaboration with external firms, universities, and research institutions. AI technologies may assist firms in identifying technological opportunities, matching knowledge elements, and screening potential partners, while these organizational arrangements can broaden knowledge sources and support collaborative development.

This paper also has limitations that suggest directions for future research. First, although the fixed-effects, Bartik IV, and pilot-zone analyses alleviate some endogeneity concerns, the results remain conditional on their identifying assumptions. Longer policy windows or alternative exogenous shocks could strengthen causal identification. Second, because the sample is limited to firms listed on the Shanghai and Shenzhen main boards, the findings may not generalize directly to smaller, unlisted, innovation-board, or non-Chinese firms. Broader samples could help assess their external validity. Third, the patent-based variables capture observable AI technological accumulation and green patenting outcomes but not firms' internal AI deployment, non-patented innovation, or actual environmental performance. Future research could combine patent data with information on AI applications, AI-related employment, R&D projects, technology commercialization, energy use, and emissions. Fourth, this paper measures knowledge fusion and technology cooperation using IPC overlap and green patent co-application information. These measures capture observable outcomes of the mechanisms, but they cannot fully reveal the dynamic processes of knowledge fusion and collaborative innovation. Future studies could use R&D cooperation contracts, supply-chain relationships, industry–university–research

projects, or interview data to further examine how AI capability affects green technological knowledge generation and cross-organizational collaboration.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182010499/s1, Table S1: Variable Definitions; Table S2: Artificial Intelligence Keyword Dictionary; Table S3: Correlation Matrix; Table S4: Correlations among Alternative AI Measures; Table S5: Robustness Check Using AI Patent Stocks; Table S6: Robustness Check: Alternative Green Innovation Outcomes; Table S7: Alternative Measures of Green Innovation Impact; Table S8: Overlap between AI Patents and Green Patents; Table S9: Sensitivity Analyses for the Bartik IV; Table S10: AI Pilot Policy Cohorts and Sample Coverage; Table S11: Policy-Shock Evidence: Dynamic Sun–Abraham Effects; Table S12: Robustness Check Controlling for Prior Green Patent Volume; Table S13: Robustness Check: High-Dimensional Fixed Effects; Table S14: Oster Coefficient Stability Test; Table S15: Alternative Levels of Clustered Standard Errors; Figure S1: Marginal Effects of AI Capability over Urban Internet Penetration.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CNIPA	China National Intellectual Property Administration
CSMAR	China Stock Market and Accounting Research
DID	Difference-in-differences
IPC	International Patent Classification
IV	Instrumental variable
MD&A	Management discussion and analysis
WIPO	World Intellectual Property Organization

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