



The Impact of Artificial Intelligence Adoption on Corporate Green Innovation: Mediating Effect of Financial Constraints

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Abstract. This study investigates the impact of artificial intelligence adoption on corporate green innovation in the context of Chinese A-share listed companies from 2014 to 2023. Drawing on signaling theory and information asymmetry, this study examined how AI adoption effect green innovation, through the mediating role of financial constraint. Using panel fixed-effects regressions, the study finds that AI adoption significantly promotes green patent activity. Mediation analysis reveals that AI adoption alleviates firms' financial constraints, thereby enabling greater investment in sustainable innovation. Furthermore, heterogeneity analysis shows that the effect is more pronounced in state-owned enterprises, which are more troubled by information asymmetry. Robustness tests using instrumental variables confirm the causal inference. These findings highlight the value of AI not only in enhancing operational efficiency but also in improving financial flexibility and facilitating green transformation in corporations. The study underscores the potential of AI as a strategic tool promoting sustainable innovation, offering practical implications for both corporate decision-making and policy design.

Keywords: artificial intelligence, green innovation, financial constraint, information asymmetry.

1 Introduction

Ever since the release of ChatGPT in November 2022, artificial intelligence has gained unprecedented hype. There is no doubt in the future AI will transform every aspect of human life and completely revolutionize how corporations conduct business and drive innovation across industries. Corporations, as the primary engines of economic activity and technological advancement, play a critical role in shaping society. It is therefore of utmost importance to understand the impact of artificial intelligence on corporate behaviors.

Currently, environmental issues around the globe are posing crucial challenges to the existence, growth and prosperity of mankind. As a key sector of society, corporations take part in the protection of the environment through green initiatives and green

innovations. While there have been numerous studies on the effect of artificial intelligence on corporate green innovation [1][2], through both operational and non-operational channels, such as dynamic capability and green culture [3][4], non-operational channels remain largely unexplored. In particular, very few scholars have addressed the role of financial constraint in the relationship between the adoption of AI and corporate green innovation.

This study aims to narrow this research gap by exploring how a corporation's adoption of AI may enhance its green innovation through the channel of financial constraint utilizing firm and year fixed effect econometric models. In addition, the study further examines factors that may influence this relationship by conducting grouped regressions based on heterogeneous firm characteristics.

2 Literature Review and Hypothesis Development

2.1 Artificial Intelligence and Corporate Green Innovation

Artificial intelligence has emerged as a critical driver of corporate behavior, especially corporate innovation in recent years [5]. While artificial intelligence is relatively a new topic, the study of green innovation dates to 2008 when Chen, Y first introduced the term [6]. Interest in the intersection between AI and green innovation has grown significantly since 2022, with a surge in related publications from 2023 to 2025. Numerous studies have examined the effect of artificial intelligence on green innovation under various contexts, generally finding a significant positive relationship [7][8]. However, the strength of the impact varies across studies and only a few channels through which the effect is transmitted have been identified.

2.2 Hypothesis Development

The integration of artificial intelligence technologies into corporates fundamentally reshaped how firms approach innovation, particularly in sustainability. AI technologies allow firms to process and analyze vast quantities of data, capturing hidden patterns and trends unable to be identified with traditional data analysis methods. This advantage empowers corporates to enhance their innovation efficiency through a variety of channels, including the adoption of improved processes and practices; the automation of labor-intensive tasks; the acceleration of research and development processes; and the enhanced ability to identify and capitalize on green innovation opportunities. Therefore, this paper proposes the following hypothesis:

H1: The adoption of artificial intelligence by corporations has a significant positive impact on their green innovation.

The efficiency with which a firm adopts artificial intelligence reflects its broader capabilities to operate, innovate, and sustain growth over the long term. Early adoption of AI and a high adoption rate serve as a strong, forward-looking signal to investors

about the firm's technological agility, strategic vision, and potential for future profitability. This signal is difficult for competitors to imitate in the short term, thereby enhancing its credibility and value in the capital market. As a result, firms demonstrating superior AI adoption efficiency are more likely to attract investor confidence and access external financing on favorable terms. This alleviation of financial constraints is particularly critical for green innovation, which often demands significant upfront investment and carries long-term, uncertain returns. By easing capital limitations through AI-enabled signaling and operational improvement, firms are better positioned to allocate resources toward green innovation initiatives. Thus, financial constraint functions as a key mediating channel through which the adoption of AI translates into enhanced corporate engagement in environmentally sustainable innovation. Therefore, this paper proposes a second hypothesis:

H2: Financial constraint serves as a mediating channel between AI adoption and green innovation.

A visual depiction of hypotheses H1 and H2 is shown in the following Figure 1.

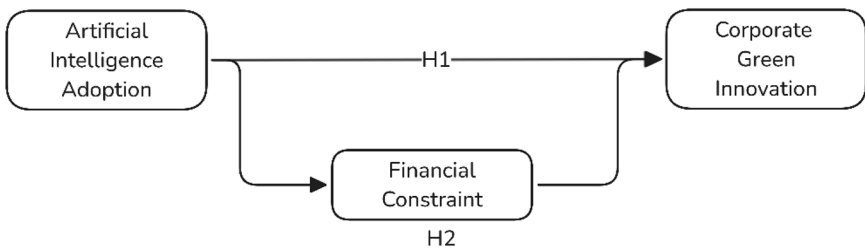


Fig. 1. Research Model.

3 Data and Method

3.1 Data and Sources

To study the effect of AI adoption on corporate green innovation, especially in Chinese companies, panel data spanning a period of 11 years from 2013 to 2023 of Chinese A-stock listed companies is used in this paper. Most data, including provincial-level CPI and per capita GDP, firm-level corporate green innovation patent applications, and corporate financial positions are sourced from CNRDS.

Using a set of 73 AI-related keywords selected via machine learning by Yao J [8], this paper obtained the number of AI-related patent applications made by each firm every year from the China National Intellectual Property Administration with Python script. This data set will serve as the indicator of a firm's level of AI adoption in this study.

Following common practice [7], companies in the finance industry and companies that have been delisted or designated as ST or *ST stocks are excluded from the sample set. In addition, observations with missing data are removed, and the main variables are

winsorized at a 1% level to remove outliers. In the end, 30,493 firm-year observations remain in the sample set. A summary description of the data is shown below in Table 1.

3.2 Main Variables

Following previous research [7], this paper uses the number of artificial intelligence patent applications (AI_Adopt) as a measurable indicator of a company’s level of AI adoption, the independent variable.

The dependent variable, green innovation (Green_Inv), is measured by the number of green patent applications, which include both invention patents and utility model patents.

Prior research identified 5 firm level control variables and 2 provincial level control variables crucial in investigating AI adoption’s impact on green innovation. These factors include firm level company size (Size), represented by the logarithmic of Total assets, asset turnover ratio (ATurn), total asset growth rate (TAG), EPS, Leverage (Lev), Tobin’s Q (TQ), and province level per capita GDP (PCGDP) and CPI.

A list of all variables used in the study is displayed below in Table 1.

Table 1. Main Variables.

	Variables	Name/Label
Independent	AI Adoption	AI_Adopt
Dependent	Green Innovation	Green_Inv
	Firm size	Size
	Total Asset Turnover	ATurn
	Total Asset Growth Rate	TAG
	EPS	EPS
Control	Leverage	Lev
	Tobin’s Q	TQ
	Per Capita GDP	PCGDP
	CPI	CPI

3.3 Modeling

Baseline Model. This study aims to assess the quantitative relationship between AI adoption, corporate green innovation and financial constraint. Baseline regression controls both industry and time fixed effects and is used to test the hypothesis that AI adoption has a positive impact on corporate green innovation.

The baseline model is constructed as follows:

$$Green_{Inv_{it}} = \alpha_0 + \beta_1 AI_{Adopt_{it}} + \Sigma \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In the model, i and t indicate year and firm. α_0 is the constant term and β_i are coefficients for each variable. $Green_Inv_{it}$ is the dependent variable, green innovation is

measured by the number of green innovation patents a company applied within each year. AI_Adopt_{it} is the independent variable, artificial intelligence adoption is measured through the number of artificial intelligence patent applications made by firms every year. $Controls_{it}$ include firm level controls size, growth, asset turnover, EPS, leverage and Tobin's Q, and province level controls Per capital GDP and CPI. μ_i and λ_t stand for firm and time fixed effects while ε_{it} is the random error term.

Mediating Model. To test the hypothesis that financial constraint will act as a non-operative mediator in AI adoption's impact on corporate green innovation, this study takes a two-step approach [9] and constructs the following model:

$$KZ_{it} = \beta_0 + \beta_1 AI_Adopt_{it-3} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

All variables have the same definition as the baseline model above, except for KZ, which stands for financial constraint and is measured with KZ Index [10][11]. The explanatory variable AI_Adopt is lagged by three periods to account for the time required for applied AI-related patents to be implemented and produce measurable effects on the firm's financial stance.

4 Result

4.1 Descriptive Statistics

Tables below reports the descriptive statistics of the main variables used in this study. Table 2 shows the descriptive statistics of the entire sample group while Table 3 describes state-owned enterprises, and Table 4 describes non-state-owned enterprises. $Green_Inv$ and AI_Adopt are winsorized at a 1% level to remove outliers. On average, companies apply for 0.918 green patents and 0.332 AI patents per year. Compared with non-state-owned enterprises, state-owned enterprises apply for more green patents and AI patents on average, but they are also larger in size. The summary statistics are consistent with previous studies.

Table 2. Descriptive statistics- All Samples

VarName	Obs	Mean	SD	Min	Median	Max
Green_Inv	30492	0.918	3.556	0.000	0.000	26.000
AI_Adopt	30492	0.332	1.385	0.000	0.000	10.000
Size	30492	22.358	1.327	14.942	22.155	28.697
ATurn	30492	0.606	0.512	-0.050	0.507	13.914
TAG	30492	0.199	3.044	-0.905	0.077	376.438
EPS	30492	0.435	1.231	-11.930	0.280	59.490
Lev	30492	1.168	4.433	-236.32	0.693	300.002
TobinQ	30492	2.160	4.645	0.611	1.649	715.945

Table 3. Descriptive statistics- State-owned Enterprises.

VarName	Obs	Mean	SD	Min	Median	Max
Green_Inv	9779	1.738	5.040	0.000	0.000	26.000
AI_Adopt	9779	0.584	1.884	0.000	0.000	10.000
Size	9779	23.076	1.464	18.370	22.942	28.697
ATurn	9779	0.625	0.549	0.012	0.502	10.586
TAG	9779	0.160	1.553	-0.905	0.059	111.548
EPS	9779	0.390	1.355	-7.140	0.240	59.490
Lev	9779	1.649	5.576	-236.32	1.019	205.890
TobinQ	9779	1.795	1.785	0.611	1.350	76.820

Table 4. Descriptive statistics- Non-state-owned enterprises.

VarName	Obs	Mean	SD	Min	Median	Max
Green_Inv	20713	0.530	2.481	0.000	0.000	26.000
AI_Adopt	20713	0.212	1.051	0.000	0.000	10.000
Size	20713	22.019	1.106	14.942	21.880	28.293
ATurn	20713	0.598	0.494	-0.050	0.509	13.914
TAG	20713	0.218	3.536	-0.899	0.087	376.438
EPS	20713	0.456	1.168	-11.930	0.300	41.000
Lev	20713	0.941	3.755	-180.56	0.585	300.002
TobinQ	20713	2.333	5.493	0.662	1.783	715.945

4.2 Regression Results

Table 5 below reports the baseline regression results. Columns (1) and (2) report baseline regression results without and with fixed effect, without adding control variables. Columns (3) and (4) report baseline regression results without and with fixed effects with control variables. Results show after controlling for fixed effects and control variables, for every 1 application of AI related patents, 0.633 green innovation patents are applied. This is consistent with the hypothesis that the adoption of artificial intelligence by corporations has a significant positive impact on their green innovation.

Table 5. Baseline Regression.

	(1)	(2)	(3)	(4)
	Green Inv	Green Inv	Green Inv	Green Inv
AI_Adopt	3.108	0.638***	1.371***	0.633***
	(267.75)	(13.40)	(114.71)	(13.38)
Size			0.615***	0.448***
			(47.84)	(7.20)
ATurn			-0.100***	0.098**
			(-3.28)	(2.14)
TAG			0.001	-0.005
			(0.21)	(-0.50)

EPS			-0.027**	0.020
			(-2.08)	(1.22)
Lev			-0.006*	-0.003
			(-1.69)	(-1.04)
TobinQ			0.014***	0.007***
			(4.13)	(2.71)
PCGDP			0.000***	0.000
			(7.32)	(0.26)
CPI			-0.106***	-0.006
			(-5.65)	(-0.14)
_cons	0.402***	0.706***	-2.764	-8.866**
	(24.14)	(44.69)	(-1.42)	(-2.06)
N	30492	30492	30492	30492
R2	0.367	0.760	0.415	0.761
Adj. R2	0.37	0.72	0.41	0.72
FE	No	Yes	No	Yes

Table 6 below reports the regression result of the mediating model. Results show a company's KZ score is inversely proportional to its adoption of artificial intelligence with a coefficient of -0.019. This implies that by adopting artificial intelligence, firms can reduce their financial constraints and gain better financial opportunities.

Table 6. Mediating Model.

	(1)
	KZ
L3.AI_Adopt	-0.019*
	(-1.86)
Size	-0.115*
	(-1.71)
ATurn	-0.015
	(-0.20)
TAG	-0.028**
	(-2.17)
EPS	-0.564***
	(-4.72)
Lev	0.022***
	(3.67)
TobinQ	0.020
	(1.43)
PCGDP	0.000***
	(3.67)
CPI	-0.018
	(-0.60)
_cons	5.050
	(1.38)

N	28040
R2	0.699
Adj. R2	0.65

4.3 Robustness

For robustness testing, using AI adoption lagged by 1 period as the instrument variable provided the results in Table 7. Column (1) shows that AI adoption in the current period is highly correlated with the instrument variable. This effect is significant at a 1% level. In column (2), the instrumental variable regression indicates that lagged AI adoption remains associated with green innovation with a coefficient of 0.433, also significant at the 1% level. These findings suggest that, even after addressing potential endogeneity concerns such as reverse causality, AI adoption continues to exert a significant positive effect on firms' green innovation performance.

Table 7. Instrument Variable.

	(1) AI Adopt	(2) Green Inv
IV	0.303*** (14.66)	0.433*** (9.77)
Size	0.096*** (5.05)	0.495*** (7.17)
ATurn	-0.014 (-0.77)	0.079 (1.63)
TAG	0.004 (0.76)	0.004 (0.24)
EPS	-0.005 (-0.77)	0.022 (1.14)
Lev	-0.001 (-1.37)	-0.007* (-1.83)
TobinQ	0.002** (2.29)	0.008*** (2.76)
PCGDP	0.000** (2.21)	0.000 (0.35)
CPI	-0.015 (-0.60)	-0.005 (-0.11)
_cons	-0.658 (-0.26)	-9.948** (-2.06)
N	27297	27297
R2	0.579	0.753
Adj. R2	0.50	0.71

4.4 Heterogeneity Testing

The result of heterogeneity testing is shown in Table 8. Columns (1) and (2) compare the impact of AI adoption on corporate green innovation. For every AI related patent application, state-owned enterprises gain 0.785 more green patents, compared with 0.424 in non-state-owned enterprises. Columns (3) and (4) compare the impact of AI adoption on financial constraints. For every AI related patent lagged 3 periods, state-owned enterprises' KZ Index changes by -0.019, compared with -0.003 in non-state-owned enterprises. By grouping samples, heterogeneity testing reveals that the positive impact of adopting AI on corporate green innovation is greater for state-owned enterprises. This difference is partially due to more financial constraints relieved in state-owned enterprises due to AI adoption compared with non-state-owned enterprises. This finding is in line with previous research that found more information asymmetry exists between managers and investors in state-owned enterprises.

Table 8. Heterogeneity testing.

	(1) Green Inv	(2) Green Inv	(3) KZ	(4) KZ
AI_Adopt	0.785*** (11.77)	0.424*** (7.54)		
L3.AI_Adopt			-0.019 (-1.35)	-0.003 (-0.22)
Size	0.719*** (5.01)	0.390*** (5.90)	0.244** (2.26)	-0.278*** (-3.60)
ATurn	0.192* (1.79)	0.046 (1.05)	-0.415*** (-2.81)	0.112 (1.51)
TAG	0.050 (1.47)	-0.012 (-1.20)	-0.026 (-1.40)	-0.027* (-1.94)
EPS	0.029 (0.53)	0.001 (0.08)	-0.385 (-1.54)	-0.634*** (-10.12)
Lev	-0.006 (-1.05)	0.001 (0.79)	0.010 (1.45)	0.037*** (3.64)
TobinQ	0.054*** (2.99)	0.004*** (3.32)	0.219*** (3.24)	0.015 (1.45)
PCGDP	-0.000 (-0.55)	0.000 (0.72)	0.000 (1.31)	0.000*** (3.40)
CPI	-0.047 (-0.57)	0.009 (0.25)	-0.131*** (-3.33)	0.060 (1.39)
_cons	-10.525 (-1.15)	-9.325** (-2.33)	8.950* (1.73)	0.059 (0.01)
N	9779	20713	9566	18474
R2	0.798	0.693	0.707	0.712
Adj. R2	0.77	0.63	0.66	0.65
SOE	Yes	No	Yes	No

5 Discussion

The empirical findings of this study supported the proposed hypotheses, offering insights into the mechanisms through which AI adoption drives corporate green innovation. First, the significant positive relationship between AI adoption and green patent output highlighted AI's role in driving sustainability across companies. Second, the mediation analysis confirms that the alleviation of financial constraints acts as a critical channel in AI's impacts. Furthermore, heterogeneity analysis reveals that the effect is more pronounced in state-owned enterprises because more information asymmetry exists between investors and managers in these firms. These findings reveal the broader strategic value of AI adoption—not just as a technological upgrade, but as a mechanism for promoting environmental responsibility.

Several constraints should be acknowledged in this study. First, although several measures have been proposed to measure a firm's financial constraint, no single measure can accurately calculate the exact financial constraint level of a firm. Second, further endogeneity testing, especially tests that can address factors that might affect AI adoption and green innovation at the same time, can improve the robustness of the test results.

6 Conclusions

This paper studied the impact of artificial intelligence adoption on corporate green innovation and the non-operational channels through which this effect is transmitted in the Chinese stock market.

Empirical results found that the adoption of AI by a company has a significant positive impact on its green innovation. This effect is transmitted through both operational channels, such as operational efficiency and enhanced decision making, and non-operational channels, particularly financial constraints.

Information asymmetry and signaling theory play a crucial role in the transmission of effect through non-operational constraints. Further heterogeneity analysis reveals that this effect is strengthened among state-owned enterprises due to more information asymmetry between investors and managers of these firms.

These findings highlight the benefits of AI adoption for corporate managers and investors. For managers, AI adoption serves as a strategic tool to boost operation efficiency, and foster innovation while simultaneously improving transparency and credibility in capital markets. For investors, the adoption of AI can be interpreted as a positive signal of a firm's long-term financial health and sustainability. Overall, this study underscores the strategic importance of AI integration in advancing sustainable innovation and enhancing corporate value in emerging economies.

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