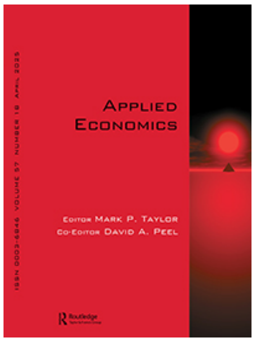

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How does artificial intelligence change carbon emission intensity? A firm lifecycle perspective

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ABSTRACT
Artificial intelligence (AI) is crucial in achieving the carbon peak and neutrality goals and mitigating climate change. Although previous studies have explored cross-sectional differences in corporate carbon emissions, temporal heterogeneities in firm lifecycles have been overlooked. Therefore, this study investigates the effect of AI adoption on carbon emission intensity over firm lifecycles and the micro-level mechanisms of this effect. This study examines panel data from Chinese listed companies (2010–2021) using a two-way fixed-effects model and the difference-in-differences method. The empirical results demonstrate that AI significantly reduces enterprises' carbon emission intensity. However, this effect is mainly observed in growth-stage enterprises and not in decline-stage enterprises. The mechanism analysis reveals that AI primarily reduces enterprises' carbon emission intensity by improving productivity and promoting innovation. The effect on productivity is particularly evident in growth-stage enterprises, whereas the effect on innovation is dominant in decline-stage enterprises. Heterogeneity tests indicate that the effect on state-owned enterprises, medium-sized enterprises, the manufacturing sector, heavily polluting industries, non-high-tech industries, and capital-intensive industries is more pronounced than that on other enterprises. These findings suggest that enterprises should actively adopt AI, and differentiated AI adoption strategies should be formulated based on the needs of enterprises at different lifecycle stages.

KEYWORDS
Artificial intelligence; carbon emission intensity; firm lifecycle; productivity

JEL CLASSIFICATION
O31; O32; O33

I. Introduction

As climate change has become a global challenge, enterprises are compelled to take proactive measures to meet carbon reduction targets (Hoogerbrugge, van de Kaa, and Chappin 2023). Among these measures, artificial intelligence (AI), a key component of the digital economy, has become a powerful tool in China, which is the world's largest carbon emitter (Z. Wang and Zhang 2024; Xu et al. 2024). As shown in Figure 1, before 2014, few enterprises used AI technologies (<100 enterprises). This number has increased since 2015. In 2021, 2,184 enterprises (nearly half of all listed companies in China) reported using AI technologies. This burgeoning trend is seen worldwide and is driven by recent breakthroughs in AI-related applications (Kinkel, Baumgartner, and Cherubini 2022).

AI helps enterprises achieve efficient and sustainable operations through data analysis, optimization, and automation (Y. Liu, Zhu, and Seuring 2020). However, whether AI can effectively reduce corporate carbon emissions remains debatable (Zhong et al. 2024). AI can optimize energy management and resource utilization, thereby reducing emissions (Zhou et al. 2021). However, the development of AI technologies can increase the demand for computational capacity, which is a source of carbon emissions (Dhar 2020).

Current research on corporate carbon emissions often considers cross-sectional differences among enterprises, neglecting temporal heterogeneities over the firm lifecycle. According to the theory of firm lifecycles, enterprises exhibit significant differences in size, profitability, growth potential, investment and financing decisions, and strategic objectives at various developmental stages (Miller and Friesen 1984). This provides a crucial perspective for understanding AI's effect on firm-level capability to reduce carbon emissions. Accounting

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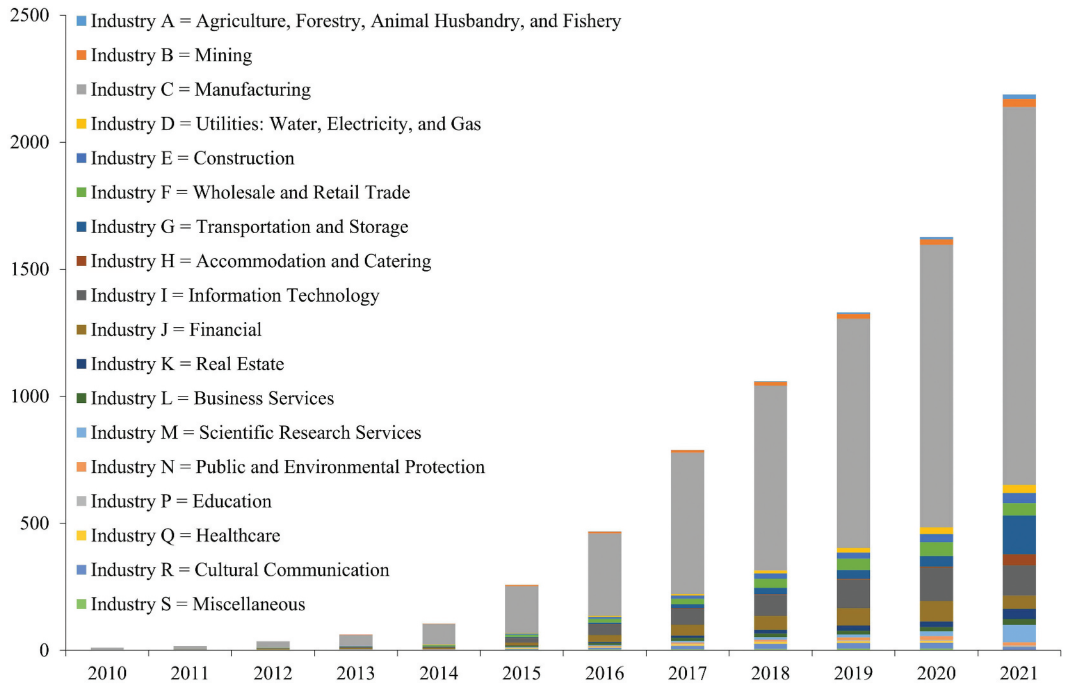

Figure 1. Number of AI-adopting enterprises in the A-share market.

for corporate lifecycles may help resolve the debate and mixed findings on AI's impact on carbon emissions. To fill the gap in the existing literature, this study examines the effect of AI adoption on corporate carbon emission intensity and aims to identify the underlying mechanisms of this effect. We pose the following research questions (RQs):

RQ1: What effect does AI have on the carbon emission intensity at different lifecycle stages?

RQ2: What are the mechanisms underlying these effects?

The study aims to make the following contributions to existing literature. First, while previous research has mainly adopted a static perspective (e.g. Zhang and Yu 2024), our paper is among the first to systematically examine AI's role in carbon reduction through the lens of Firm Lifecycle Theory. By distinguishing between growth-stage, mature, and decline-stage firms, this research moves beyond static analyses and develops a dynamic framework that captures the heterogeneous effects of AI adoption on corporate carbon emission intensity. Second, this study novelly identifies two distinct mechanisms – improving productivity and fostering innovation, through which AI reduces carbon emission intensity. We further reveal that growth-stage firms benefit more from productivity improvements, while decline-stage firms benefit more from innovation enhancement. This refinement helps resolve the divergent results at industrial or regional levels in prior literature (e.g. Chen et al. 2022; Yu et al. 2023). Firm-level evidence also provides practical insights to develop more targeted AI application strategies for firms across different lifecycles.

II. Literature review

Existing studies on AI and carbon emission intensity primarily focus on the industrial and regional levels (see the Supplementary Materials for a detailed literature review). At the industry level, proxies such as industrial robots and AI publications indicate reduced carbon intensity (J. Liu et al. 2022). In contrast, regional analyses present mixed findings. Proxies based on industrial robots have shown lower carbon intensity at provincial and municipal levels than at regional levels (Tao, Wang, and Zhai 2023), whereas those using AI publications have revealed rebound effects, such as initial increases in electricity use and carbon emissions followed by declines (Xue, Liu, and Fu 2022). However, firm-level analyses remain scarce, despite evidence indicating that lifecycle stages influence AI adoption, innovation, firm value, and risk (Song and Xie 2022). Our study fills this gap in the literature by adopting a firm-level perspective to investigate the dynamic impact of AI on carbon intensity. We develop testable hypotheses by combining two strings of literature on carbon intensity emissions and corporate lifecycles.

AI can achieve real-time monitoring and fine management of carbon emission sources through data analysis and machine learning algorithms, thereby promoting scientific management and control of carbon emissions in enterprises (Xue, Liu, and Fu 2022). This influence has been validated in various fields, such as helping enterprises achieve efficient energy utilization and management, promoting transitions to low-carbon economic models, optimizing energy consumption, and encouraging green energy use (Huang and Zhou 2025). In smart manufacturing, smart grids improve energy efficiency and provide timely power at optimal costs (Palomares et al. 2021). Therefore, we propose the following hypothesis:

H1: AI significantly reduces carbon emission intensity.

AI use does not necessarily directly change carbon emission intensity; it requires adjustments in related production processes, technologies, and even personnel, which may entail additional costs and risks. Enterprises at different lifecycle stages have varying attitudes towards costs and risks, leading to varying impacts of AI on carbon emission intensity. According to the enterprise lifecycle theory, companies have diverse operational goals and methods at various developmental stages (Miller and Friesen 1984).

Growth-stage enterprises aim to increase their market share and diversify their product lines by continuously expanding their production, sales forces, and distribution systems. They are willing to diversely experiment, take risks, and face many investment opportunities (Zhang and Yu 2024). These enterprises may adopt new technologies to improve efficiency, reduce costs, and meet market demand. Therefore, growth-stage enterprises are likely to invest resources in new technologies, thereby achieving environmental and economic benefits. From a financing perspective, growth-stage enterprises have significant capital needs. To attract external investors, they may focus on efficiency and resource utilization, optimize production processes, and reduce material waste, thereby lowering carbon emission intensity. Therefore, we propose the following hypothesis:

H2a: AI effectively reduces carbon emission intensity in growth-stage enterprises.

In the mature stage, enterprises achieve stable growth, profitability, and cash flow, usually by securing a specific market share. Their operational goals are often to maintain market share and profitability, pursue product differentiation, maximize profits, and focus on stability more than on aggressive expansion. Therefore, mature-stage enterprises may not be willing to invest in environmental technologies and practices. Established production and operational modes, institutionalized management processes, and formal organizations hinder the implementation of AI and carbon reduction technologies without encountering internal resistance and adaptation issues (Gu and Peng 2022), thus reducing the likelihood and degree of lowering carbon emission intensity. Therefore, we propose the following hypothesis:

H2b: AI does not effectively reduce carbon emission intensity in mature-stage enterprises.

In the decline stage, products or services become outdated, and market share and sales decrease. These enterprises may face outdated production equipment, lagging technology, reduced flexibility, and institutional rigidity (J. Liu et al. 2022). Survival is the primary concern when facing the risk of restructuring or market exit. Enterprises may adopt conservative or radically transformative strategies. They may focus on survival and financial stability, deprioritize environmental considerations, and lack sufficient resources to invest in environmental technologies. Therefore, we propose the following hypothesis:

H2c: AI does not effectively reduce carbon emission intensity in decline-stage enterprises.

Labour productivity is a crucial indicator of economic performance. By improving labour productivity, enterprises can achieve higher output with the same labour input, reduce costs, use resources and energy more efficiently, and promote sustainable economic growth. AI fundamentally substitutes and supplements human capital; enables automation and robotics to replace labour in repetitive, tedious, or dangerous tasks; reduces material waste; enhances production efficiency; and lowers carbon emissions per unit output (X. Li and Tian 2023). For instance, automated sorting systems using robots and intelligent conveyers reduce manual handling, retention time, energy consumption, and carbon emissions and increase logistics efficiency. Therefore, we propose the following hypothesis:

H3a: AI reduces carbon emission intensity by improving labour productivity.

From the enterprise lifecycle perspective, growth-stage enterprises actively explore new markets and expand rapidly, requiring labour and capital to meet market demands. In the mature and decline stages, productivity has reached high levels, and enterprises may not prioritize productivity due to operational goals. This limits the potential of AI to reduce carbon emission intensity through productivity improvements. Therefore, we propose the following hypothesis:

H3b: AI significantly affects carbon emission intensity of growth-stage enterprises by improving their productivity.

AI fosters innovation by improving R&D efficiency, accelerating innovation, optimizing systems and processes, and providing predictive and decision support. It enables enterprises to complete complex tasks, allowing employees to focus on creativity and innovation, and enhances carbon emission management. Innovation accelerates the adoption and use of renewable energy and equipment, improve traditional energy efficiency, and enhance new energy utilization, thereby contributing to carbon reduction (Huang and Zhou 2025). By introducing AI, enterprises can develop efficient low-carbon products, improve their energy-use patterns, and optimize their production processes to reduce energy consumption and carbon emission intensity. Therefore, we propose the following hypothesis:

H3c: AI reduces carbon emission intensity by promoting innovation.

In the decline stage, enterprises face market pressure and must re-evaluate their strategies and operations, undergoing strategic transformations to adapt to changing market demands. AI can trigger innovation and help enterprises find new opportunities during difficult periods. New products and services resulting from innovation tend to be environmentally friendly. Therefore, we propose the following hypothesis:

H3d: AI significantly affects carbon emission intensity of decline-stage enterprises by improving their innovation.

Although previous studies have focused on the lifecycle stages of enterprises, their cross-sectional heterogeneity must also be considered. AI's impact on carbon emission intensity may vary depending on enterprise and industry characteristics. For instance, state-owned enterprises may receive government support, bear social responsibility, and invest in AI to reduce carbon emissions and enhance sustainable development. Medium-sized enterprises that balance expansion and stability may leverage AI to optimize production and improve efficiency. Small enterprises with limited resources may not be able to afford the high costs of implementing environmental technologies, whereas large enterprises with established systems may face integration challenges. Manufacturing enterprises involve complex processes that can be optimized using AI to reduce energy consumption and carbon emissions. High-pollution industries face strict environmental regulations and policies, which drive them to adopt AI to reduce their carbon emissions. Non-high-tech industries that rely on traditional energy sources may benefit from AI optimization to reduce waste. Capital-intensive industries that rely on significant capital equipment may use AI to reduce their energy consumption. Therefore, we propose the following hypothesis:

H4: The impact of AI on carbon emission intensity varies based on enterprise and industry characteristics at different lifecycle stages.

III. Research design

Models

This study follows Moser and Voena (2012) and employs a two-way fixed-effects model complemented by a difference-in-differences (DID) approach. This methodological framework is widely used in empirical studies to assess policy interventions and technological adoption effects, as it effectively accounts for time-invariant firm heterogeneity and common shocks over time (Angrist and Pischke 2009; Wooldridge 2010). The following baseline econometric model is used:

$$CI_{i,t} = \alpha_0 + \alpha_1 Treat_i * Post_t + \alpha_n X_{i,t-1} + \delta_t + u_i + v_{i,t} \tag{1}$$

where $CI_{i,t}$ is the carbon emission intensity of enterprise i in year t; α_0 is the constant term; $Treat_i$ is a dummy variable indicating whether enterprise i has applied AI at least once between 2010 and 2021 (1 = yes, 0 = no); $Post_t$ is a dummy variable indicating whether year t is after the AI adoption (1 = yes, 0 = no); the interaction term $Treat_i * Post_t$ indicates the treatment effect (impact of AI adoption on carbon emission intensity); $X_{i,t-1}$ represents control variables at the enterprise level, lagged by one period; α_n is the coefficient for the control variables; δ_t represents year fixed effects to control for time-specific effects; u_i represents enterprise fixed effects to control for time-invariant unobserved heterogeneity across enterprises; and $v_{i,t}$ is the error term representing the overall market random disturbances. Notably, $Treat_i$ and $Post_t$ are absorbed by the enterprise fixed effects u_i and year fixed effects δ_t and do not appear separately in the model. This helps mitigate unobserved heterogeneity and omitted variable bias, strengthening the causal interpretation of AI's impact (Imbens and Wooldridge 2009).

To address the endogeneity issue, this study employs instrumental variable and event study methods. First, the probabilities of AI adoption in the industry and industry region (both excluding the focal firm) are used as instrumental variables for the firm's AI adoption (Quan et al. 2023). This approach examines the impact of omitted variables and reverse causality on the regression results.

Subsequently, we use the event study method to confirm the parallel trends assumption. Following Xu and Yao (2015), we use the event study method to assess the distribution of AI's impact. An enterprise's AI adoption is defined as the event of interest. The year of AI adoption is defined as year 0, with the years before and after adoption labelled −1, −2, and −3 and 1, 2, and 3, respectively. This generates a dummy variable, $Treat_{i,t}$, which represents whether enterprise i adopted AI in year t. Substituting this into Model (2) allows us to estimate the dynamic changes in AI's impact over the years surrounding the adoption event.

$$CI_{i,t} = \alpha_0 + \alpha_1 Treat_{i,t} + \alpha_n X_{i,t-1} + \delta_t + u_i + v_{i,t} \tag{2}$$

Based on a theoretical analysis, AI may impact carbon emission intensity through increased labour productivity and innovation. To further explore the mechanisms of AI's impact, this study constructs mediation effect models drawing on Jiang's (2022) methodology. The following econometric models are used:

$$M_{i,t} = \eta_0 + \eta_1 Treat_i * Post_t + \eta_n X_{i,t-1} + \delta_t^m + \mu_i^m + v_{i,t}^m \tag{3}$$

$$CI_{i,t} = \beta_0 + \beta_1 Treat_i * Post_t + \beta_2 M_{i,t} + \beta_n X_{it-1} + \delta_t^c + \mu_i^c + v_{i,t}^c \tag{4}$$

where $M_{i,t}$ represents the mediator variables, specifically labour productivity and innovation. The models aim to test whether the impact of AI on carbon emission intensity is mediated by these variables.

Measures

This defines the dependent, independent, and mediating variables. A detailed description of the control variables is presented in the Supplementary Materials.

Dependent variable

Following the mainstream method in the existing literature, we measure corporate carbon emission intensity as the ratio of total carbon emissions to operating revenue (J. Wang, Wang, and Wang 2022). According to the greenhouse gas protocol, a company's carbon emissions are categorized into three scopes:

- **Scope 1**: Direct greenhouse gas emissions from sources owned or controlled by the company. These include stationary combustion from boilers for heating buildings, mobile combustion from vehicle fuel use, fugitive emissions such as methane from coal mines and ventilation systems, and process emissions from industrial manufacturing.
- **Scope 2**: Indirect greenhouse gas emissions from consumption of purchased electricity, steam, heating, and cooling.
- **Scope 3**: Other indirect emissions not covered in Scope 2, including emissions from upstream and downstream activities such as transportation of purchased fuels, employee commuting, and using sold products and services.

Scope 1 and 2 emissions must be disclosed under the greenhouse gas protocol, and their sum is typically reported as the company's total carbon emissions. This study adopts this measure to calculate total corporate carbon emissions.

Independent variable

Listed companies typically disclose significant operational information in their annual reports. This study conducts a text analysis of annual reports to extract information on AI technology applications. Keywords such as 'artificial intelligence', 'AI', and 'intelligent manufacturing' are used to identify relevant disclosures. The selection of artificial intelligence technology keywords mainly refers to the White Paper on Artificial Intelligence Standardization (2018 edition) issued by the China Institute of Electronic Technology Standardization. Subsequently, we conduct a manual review to verify whether the company implemented AI in a given year. The constructed binary AI variable indicates whether a company implemented AI in a particular year, corresponding to the interaction term $Treat_i * Post_t$ in the baseline model. If a company applied AI at any point during the sample period, the variable is set to one for that year and subsequent years; otherwise, it is set to zero for all years.

Two critical concerns regarding the AI variable derived from text analysis are the reliability of keyword search results and potential biases in manual verification. To mitigate the first issue, this study constructs a keyword list based on a comprehensive review of relevant literature and industry reports, ensuring its relevance and accuracy in identifying AI applications. Moreover, sensitivity tests are conducted by varying keyword combinations, confirming the robustness of the results. For the second issue, a double-blind review process is implemented during manual verification. Two independent reviewers assess the identified AI-related texts, and any discrepancies are resolved through discussion or, if necessary, by consulting a third reviewer. This approach minimizes subjective bias and enhances the reliability of the manual verification process.

Mediating variables

Labour productivity (LP) is measured using the natural logarithm of the per capita operating revenue (Niu, Chen, and Lin 2023). Labour productivity represents the value or output generated by a company per unit of time, reflecting the company's production efficiency and operational performance. Innovation (RD) is measured using the natural logarithm of R&D expenditure. Companies' R&D expenditures reflect the intensity of their investments in innovative activities. Higher R&D expenditures indicate higher levels

Table 1. Cash flow combinations at different lifecycle stages.

	Growth			Decline				
Cash Flow Type	Introduction	Growth	Maturity	Decline	Decline	Decline	Elimination	Elimination
Operating Cash Flow	−	+	+	−	+	+	−	−
Investing Cash Flow	−	−	−	−	+	+	+	+
Financing Cash Flow	+	+	−	−	+	−	+	−

of innovation. Although some studies have used the number of patent applications as an outcome measure of innovation, this indicator often has many missing values, and the absence of patent applications does not necessarily imply a lack of innovation. Therefore, this study uses a process-based indicator instead of an outcome-based one (C. Li et al. 2023).

Corporate lifecycles

Following the cash flow pattern method, companies are categorized into three lifecycle stages: growth, maturity, and decline (Zhang and Yu 2024). Cash flow characteristics at each stage are presented in Table 1.

Data

This study uses data from Chinese A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2010 to 2021. The main sources of sample data are the Global Trade Analysis database, annual disclosure data from listed companies, and the National Bureau of Statistics of China. Operating, scale, and innovation data are obtained from the Global Trade Analysis database. Carbon emission data are sourced from annual reports, corporate social responsibility reports, company websites, environmental department websites, and the annual disclosure data of listed companies. The other variables are sourced from the China Statistical Yearbook, China Environmental Statistical Yearbook, China City Statistical Yearbook, and China Energy Statistical Yearbook. Samples with missing financial data, special treatment, and particular transfer are excluded, and all continuous variables in the regression are winsorized at the top and bottom 1% to mitigate the influence of outliers.

Table 2 presents the descriptive statistics of the main variables. Carbon emission intensity is approximately 475 kg per 10,000 yuan of operating revenue over the past decade. The average value of AI adoption is 0.23, indicating that approximately 23% of firm-years implemented AI. The descriptive statistics of other variables fall within reasonable ranges.

Table 3 categorizes firms into growth, mature, and decline stages; reports observations and mean values for the key variables; and presents the results of independent t-tests between groups. Growth-stage firms are the most numerous and exhibit the highest carbon emission intensity, whereas mature-stage firms are the least numerous and have the lowest intensity. Mature-stage firms rank the highest in AI adoption, labour productivity, innovation, employment scale, asset turnover, and return on assets. Firm age increases from growth to decline. The t-test results identify significant differences in these variables across lifecycle stages.

Table 2. Descriptive statistics.

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
CI	Carbon Emission Intensity	24,755	475.3	206.2	152.9	1870.6
AI	Artificial Intelligence (0 or 1)	24,755	0.23	0.42	0	1
lnLP	Labor Productivity (log)	24,332	4.60	0.76	2.90	6.96
lnRD	Technological Innovation (log)	18,401	17.85	1.37	13.59	21.90
AGE	Firm Age (years)	24,755	9.61	7.46	0	31
lnEM	Employment Scale (log)	24,755	7.73	1.23	4.73	11.24
lnTA	Total Assets (log)	24,755	21.16	3.16	11.62	26.16
LEV	Leverage Ratio	24,755	0.42	0.20	0	0.89
DTR	Asset Turnover Ratio	24,755	0.64	0.39	0	2.34
ROA	Return on Assets	24,755	0.06	0.07	−0.16	0.37
REVE	Revenue Growth Rate	24,755	0.18	0.37	−0.50	2.47
CR	Ownership Concentration	24,755	0.35	0.15	0.09	0.73
CAID	Capital Intensity	24,755	60.25	98.10	1.78	682.13
ER	Environmental Regulation Intensity	24,755	0.002	0.002	0.000	0.008
IS	Industrial Structure (%)	24,755	41.91	8.68	16.16	55.57

Table 3. Descriptive statistics by firm life cycle.

	Growth		Maturity		Decline		Growth-Maturity	Growth-Decline	Maturity-Decline
Variable	Obs.	Mean	Obs.	Mean	Obs.	Mean		t-stat	
Carbon Emission Intensity	11,527	496.0	8,855	445.9	4,273	480.2	17.253***	3.888***	−10.539***
Artificial Intelligence (0 or 1)	11,527	0.21	8,855	0.24	4,273	0.23	−5.124***	−1.806*	2.138**
Labor Productivity (log)	11,345	4.57	8,730	4.62	4,157	4.62	−4.467***	−3.679***	−0.257
Technological Innovation (log)	8,834	17.84	6,594	17.96	2,917	17.63	−5.730***	7.115***	10.890***
Firm Age (years)	11,527	8.28	8,855	10.38	4,273	11.47	−20.416***	−24.247***	−7.845***
Employment Scale (log)	11,527	7.76	8,855	7.89	4,273	7.34	−7.655***	19.449***	24.208***
Total Assets (log)	11,527	21.33	8,855	21.17	4,273	20.69	3.685***	11.508***	7.814***
Leverage Ratio	11,527	0.45	8,855	0.39	4,273	0.40	19.309***	12.393***	−2.468**
Asset Turnover Rat.	11,527	0.65	8,855	0.67	4,273	0.55	−2.790***	15.007***	16.671***
Return on Assets	11,527	0.06	8,855	0.07	4,273	0.05	−11.505***	15.627***	21.827***
Revenue Growth	11,527	0.23	8,855	0.14	4,273	0.12	17.467***	15.990***	3.876***
Ownership Concentration	11,527	0.35	8,855	0.37	4,273	0.34	−9.160***	3.420***	10.000***
Capital Intensity	11,527	57.69	8,855	70.01	4,273	47.21	−8.531***	6.596***	12.097***
Environmental Regulation Intensity	11,527	0.002	8,855	0.002	4,273	0.002	1.061	5.190***	4.162***
Industrial Structure	11,527	42.44	8,855	41.80	4,273	40.73	5.215***	11.044***	6.600***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

IV. Empirical analysis

Baseline results

Table 4 presents baseline regression results on the impact of AI on corporate carbon emission intensity. As shown in Column (1), after controlling for time and firm fixed effects, AI adoption significantly reduces carbon intensity. AI lowers carbon emissions by approximately 9 kilograms per 10,000 yuan of revenue on average, supporting H1. This micro-level evidence supports previous findings at the industrial and regional levels (Tao, Wang, and Zhai 2023).

Columns (4)–(6) report the baseline regressions by firm lifecycle stage. For growth-stage firms, AI significantly reduces carbon intensity by approximately 15 units, supporting H2a. In contrast, the effects on mature- and decline-stage firms are not significant, supporting H2b and H2c. This variation across stages aligns with regional patterns of inverted U-shaped effects and 'initial increase followed by decline' (Meng and Zhao 2023), likely reflecting regional heterogeneity in firm characteristics.

Notably, AI adoption significantly reduces carbon emission intensity among growth-stage firms, whereas decline-stage firms experience a much weaker effect. This disparity arises from differences in financial resources, investment behaviours, and strategic priorities. Growth-stage firms invest in AI to boost productivity, cut costs, and improve energy efficiency through automation and optimized resource allocation, thereby lowering emissions. In contrast, decline-stage firms face financial constraints, outdated technology, and organizational rigidity, which limit AI's effectiveness despite occasional innovation. This suggests the need for tailored strategies of AI implementation, such as enhancing productivity in growth-stage firms and providing targeted support to decline-stage firms.

Table 4. Baseline regression results.

Variables	(1) Full Sample	(2) Growth	(3) Maturity	(4) Decline
AI	−9.404*	−15.460*	−1.851	−21.042
	(−1.906)	(−1.708)	(−0.305)	(−1.499)
AGE	4.911	−1.357	−1.381	19.910
	(1.039)	(−0.175)	(−0.167)	(1.544)
lnEM	−30.276***	−33.294***	−9.260	−23.664
	(−4.830)	(−3.330)	(−0.912)	(−1.641)
lnTA	13.703**	8.088	−1.680	26.682*
	(2.271)	(0.815)	(−0.158)	(1.682)
LEV	37.819**	15.365	102.831***	−23.115
	(2.249)	(0.569)	(3.693)	(−0.434)
DTR	−40.016***	−48.528***	−53.697***	−69.520**
	(−4.325)	(−3.252)	(−4.297)	(−2.547)
ROA	150.352***	279.822***	−47.078	27.915
	(4.724)	(4.481)	(−1.038)	(0.370)
REVE	93.174***	81.673***	108.350***	134.847***
	(15.330)	(8.976)	(8.901)	(8.072)
CR	45.171	55.867	11.797	8.793
	(1.561)	(1.271)	(0.237)	(0.097)
CAID	−0.116***	−0.159***	−0.031	0.022
	(−3.190)	(−2.804)	(−0.543)	(0.185)
ER	−890.624	−40.744	586.697	−785.991
	(−0.697)	(−0.017)	(0.368)	(−0.199)
IS	−0.549	−0.799	0.213	1.098
	(−0.719)	(−0.607)	(0.204)	(0.446)
Constant	419.141***	630.612***	517.751**	−31.062
	(3.369)	(3.163)	(2.371)	(−0.081)
Time FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	24,755	11,527	8,855	4,273
R^2	0.056	0.060	0.063	0.088

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses.

Endogeneity issues

This study faces two main endogeneity issues: omitted variables and reverse causality. The former arises because unobservable variables may influence firms' AI adoption and carbon emission intensity. The latter pertains to the bidirectional relationship, in which AI adoption may promote energy conservation and emission reduction, while the pressure to reduce carbon emissions may incentivize firms to adopt AI. We address the impact of endogeneity issues using two methods: instrumental variables and parallel trend tests.

Instrument variables

This study follows Quan et al. (2023) and employs two instrumental variables to identify the impact of AI adoption. Instrumental variable 1 is the average probability of AI adoption among other firms in the same industry, excluding the focal firm. Instrumental variable 2 is the average probability of AI adoption among other firms in the same industry and region, excluding the focal firm. The fundamental logic behind these instrumental variables is identical: both metrics influence the likelihood of a single firm adopting AI without a direct effect on the carbon emission intensity of an individual firm.

The regression results are presented in Columns (2) and (3) of Table 4. The regression coefficients of the instrumental variables are −9.402 and −11.000, respectively, and both are significant. Comparing these results with the two-way fixed-effects estimates in Column (1), the regression results for instrumental variables are highly consistent in terms of both coefficient magnitude and statistical significance. This indicates that the endogeneity concerns raised earlier do not lead to severe estimation bias.

Parallel trend test

If the parallel trend test is satisfied, the two-way fixed-effects model resembles a multi-period DID design. We define the year of AI adoption as Year 0, with Years −1–-3 preceding and Years 1–3 following, using the pre-adoption year as the baseline. Figure 2(a–d) illustrate the changes in carbon emission intensity for the full sample and growth-, mature-, and decline-stage firms. Before AI adoption, the yearly coefficients are insignificant, confirming the parallel trend. For the full sample, the coefficients are negative from Year 0 and significant in Years 0 and 1; for growth-stage firms, they are negative and significant in Years 2 and 3, whereas mature- and decline-stage firms exhibit no significant changes.

Thus, no significant change in carbon emission intensity occurs before AI adoption. After AI adoption, carbon emission intensity significantly decreases, particularly in growth-stage firms. This substantiates the parallel trend assumption, establishes a causal relationship between AI and carbon emission intensity, and partially excludes potential bidirectional causality issues. This further confirms the robustness of the baseline regression results estimated using the two-way fixed-effects model.

Recent studies have questioned the validity of the two-way fixed-effects model due to issues with selecting a control group. The control group includes all non-intervention samples in the current period. In this study, if the control group comprises firms that do not newly apply AI in the current period, it may include firms that have previously applied AI. As the effects of AI can last for several years, the dependent variable of some samples in the control group would already be influenced by AI, potentially underestimating AI's impact. Callaway and Sant'anna (2021) proposed a new method to address this issue by excluding samples that had previously applied AI from the control group. Figure 3 presents the dynamic impact of AI on carbon emission intensity using the DID method. The results show a significant reduction in carbon emission intensity after AI adoption, with the parallel trend holding.

Robustness

The robustness of our conclusions is influenced by the reliability of the variables, rationality of the samples, and effects of other technologies. Drawing on the existing literature (J. Wang, Wang, and Wang 2022), we adopt the following methods to conduct robustness checks on the estimation results.

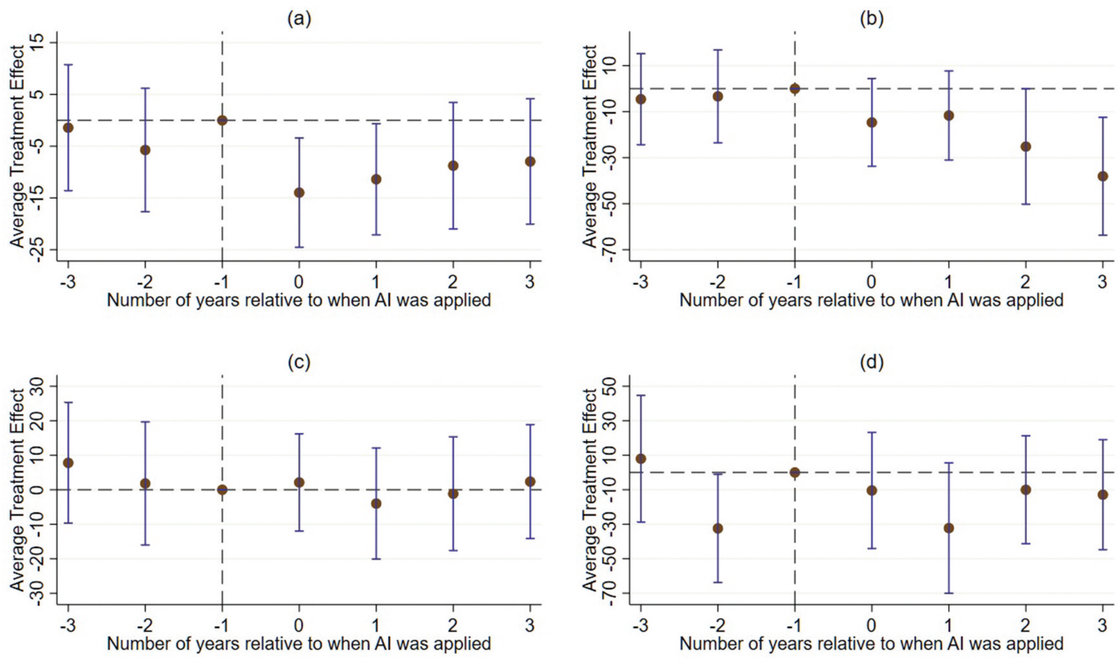

Figure 2. Dynamic impact of AI on carbon emission intensity. (a) Full sample, (b) Growth, (c) Maturity, (d) Decline.

Replacing the dependent variable measure

To ensure comparability, carbon emission intensity is recalculated using Scope 2 emissions (purchased electricity, steam, heating, and cooling). Electricity is a major emission source. As shown in Panel A of Table 5, AI significantly reduces intensity for the full sample. The AI coefficient remains significant, which is consistent with the baseline findings.

Changing the method of enterprise lifecycle division

Beyond the cash flow method, we classify lifecycles using a comprehensive index based on four indicators: revenue growth, retained earnings, capital expenditure ratios, and enterprise age (J. Liu et al. 2022). We rank expenditure and revenue growth from high to low, and retained earnings and age from low to high, scoring by percentiles and summing. Using cash flow proportions, we reclassify

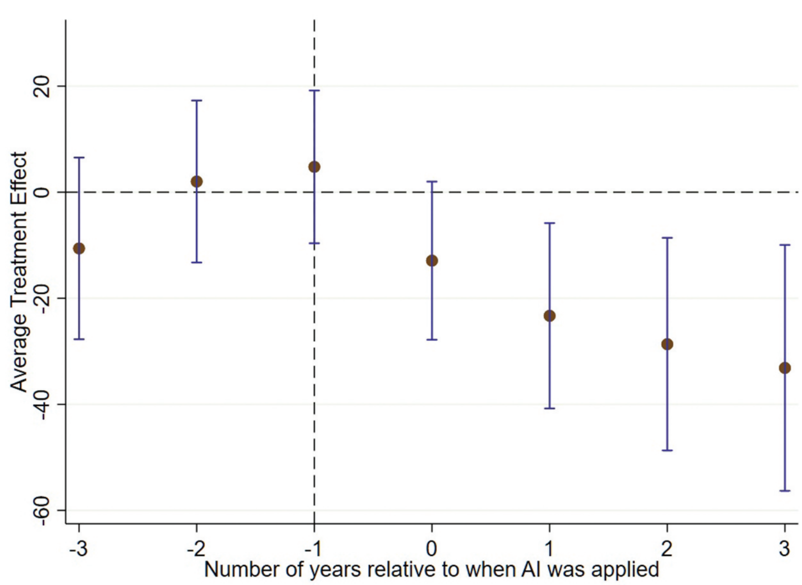

Figure 3. Dynamic impact of AI on carbon emission intensity based on DID estimation.

Table 5. Robustness results.

	(1) Full	(2) Growth	(3) Maturity	(4) Decline
Panel A				
AI	−1.524*	−2.527*	−0.834	−2.993
	(−1.918)	(−1.820)	(−0.755)	(−1.157)
Observations	24,751	11,529	8,848	4,274
R^2	0.044	0.051	0.043	0.067
Panel B				
AI	−9.404*	−9.585*	−16.328	6.604
	(−1.906)	(−1.673)	(−1.582)	(0.328)
Observations	24,755	16,127	6,185	2,443
R^2	0.056	0.061	0.052	0.076
Panel C				
AI	−9.195*	−15.689*	−1.778	−19.267
	(−1.857)	(−1.728)	(−0.292)	(−1.372)
Observations	24,556	11,449	8,784	4,226
R^2	0.056	0.059	0.063	0.093
Panel D				
AI	−9.594*	−16.763*	−0.714	−19.313
	(−1.936)	(−1.802)	(−0.120)	(−1.499)
Observations	22,801	10,608	8,400	3,695
R^2	0.053	0.06	0.059	0.083
Panel E				
AI	−9.336*	−15.463*	−1.6	−20.271
	(−1.891)	(−1.708)	(−0.264)	(−1.451)
Observations	24,751	11,526	8,854	4,271
R^2	0.056	0.06	0.063	0.09
Panel F				
AI	−9.092*	−15.078*	−1.977	−20.472
	(−1.838)	(−1.662)	(−0.326)	(−1.453)
Observations	24,736	11,519	8,849	4,268
R^2	0.056	0.06	0.063	0.089

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses. All regressions have control variables, time fixed effects, and firm fixed effects.

the lifecycles. As shown in Panel B of Table 5, the results confirm our conclusions.

Changing the sample

To address systematic differences in carbon emissions, this study excludes samples from underdeveloped regions (Qinghai Province, Tibet Autonomous Region, and Xinjiang Uyghur Autonomous Region) and non-industrial sectors (construction and real estate industries). Panels C and D of Table 5 present the results. The AI coefficients are negative and significant for the full sample and growth-stage firms, whereas they are not significant for mature- and decline-stage firms. These findings align with the baseline regression results.

Testing for omitted variables

To address the potential omitted variable bias, we examine additional factors affecting carbon emission intensity. First, we include enterprise ownership as a control variable, as state-owned firms often receive government support, assume social responsibility, and are inclined to invest in AI to reduce emissions. Second, we control for the adoption of other digital technologies, measured using a text search for 'digital technology', 'digital network', and 'data mining' in annual reports (Zhao et al. 2024). As shown in Panels E and F of Table 5, the AI coefficients for the full sample and growth-stage firms remain significant, which is consistent with the baseline regression results.

Counterfactual methods

We employ three counterfactual methods for placebo tests to reinforce the robustness of our findings.

Shifting the year of initial AI adoption

We artificially change the treatment timing to two years before, one year before, one year after, and two years after the actual year of AI adoption as the supposed year of adoption. Using Econometric Model (1), we examine whether AI's impact on carbon emission intensity remains significant. As shown in Table 6, none of the coefficients are significant, confirming the identified treatment effect.

Randomly changing the year of initial AI adoption

Assuming that the firms that adopted AI remain unchanged, we randomly select any year between 2010 and 2021 as the initial AI adoption year for these firms. The AI impact coefficients in Model (1) are estimated using the new sample. This process is repeated 1,000 times. As shown in Figure 4(a), the mean of the coefficients is close to zero and follows a normal distribution, indicating no significant effect.

Table 6. Placebo test results.

	(1)	(2)	(3)	(4)
	Carbon Emission Intensity			
AI (Two Years Before)	−1.641			
	(−0.325)			
AI (One Year Before)		−0.555		
		(−0.117)		
AI (One Year After)			−2.674	
			(−0.552)	
AI (Two Years After)				1.584
				(0.334)
Observations	24,755	24,755	24,756	24,756
R2	0.056	0.056	0.056	0.056

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses.

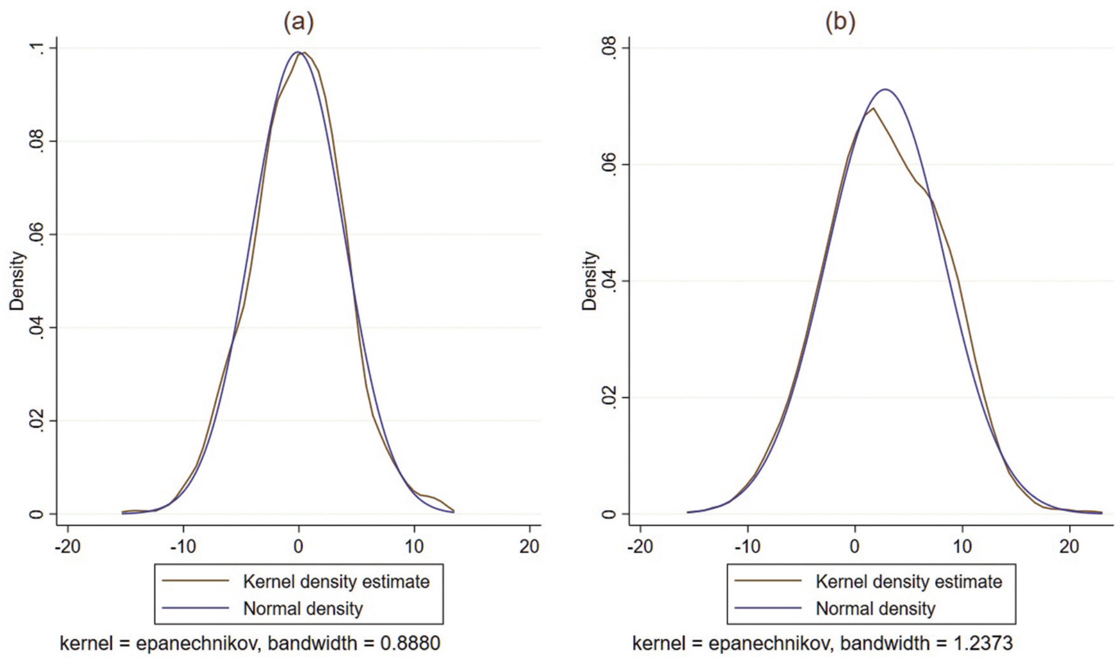

Figure 4. Placebo test (regression coefficient distribution). (a) Randomly changing the adoption year, (b) Randomly changing the treatment group.

Randomizing treatment and control groups

Firms in the original treatment group that have adopted AI are considered as the new control group. Random samples of firms are then drawn as the new treatment group based on the number of new AI adopters each year from 2010 to 2021. Model (1) is used to estimate AI's impact, and this process is repeated 1,000 times. As shown in Figure 4(b), the mean of the coefficients is 2.93, which differs significantly from the baseline regression's −9.404, and is approximately normally distributed.

Mechanism tests

We examine whether AI impacts productivity and innovation using Models (3) and (4). Table 7 shows the regression results for the mediation effects.

The productivity mechanism

For the full sample, Column (1) reports a significantly positive AI coefficient, whereas Column (2) shows a labour productivity coefficient of −78.163. This suggests that AI reduces carbon emission intensity by improving labour productivity, supporting H3a. For growth-stage firms, Column (3) indicates a significantly positive AI coefficient, whereas Column (4) reports a labour productivity coefficient of −105.678, supporting H3b. In contrast, labour productivity has no significant effect on mature- and decline-stage firms, as shown in Columns (6) and (8). At the industry and regional levels, productivity improvements through process optimization (Bloomfield et al. 2021), labour substitution (X. Li and Tian 2023), increased output (J. Liu et al. 2022), and enhanced energy efficiency (Yu et al. 2023) are key to reducing emissions.

The innovation mechanism

As shown in Column (1), the AI coefficient for the full sample is significantly positive. As shown in Column (2), after controlling for innovation, the AI coefficient is significantly negative, with an innovation coefficient of −8.462, supporting H3c. For decline-stage firms, Column (7) reports a significantly positive AI coefficient, whereas Column (8) indicates an insignificant AI effect and significantly negative innovation coefficient (−18.821), supporting H3d. Similarly, industry- and region-level mechanisms, whether through increased R&D (X. Li and Tian 2023) or structural optimization and green technology (Chen et al. 2022), suggest that AI's micro-level impact depends on enhancing innovation efficiency.

Table 7. Mediation effect regression results.

	Full Sample		Growth		Maturity		Decline	
Panel A	(1) lnLP	(2) CI	(3) lnLP	(4) CI	(5) lnLP	(6) CI	(7) lnLP	(8) CI
AI	0.028***	−7.354	0.024***	−12.600	0.007	−2.947	0.067***	−22.349
	(4.466)	(−1.487)	(2.881)	(−1.382)	(0.874)	(−0.491)	(2.927)	(−1.590)
lnLP		−78.163***		−105.678***		−25.559		−21.861
		(−7.368)		(−6.308)		(−1.329)		(−0.874)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	24,727	24,332	11,537	11,345	8,822	8,730	4,263	4,157
R^2	0.791	0.062	0.815	0.067	0.836	0.063	0.720	0.094
	Full Sample		Growth		Maturity		Decline	
Panel B	(1) lnRD	(2) CI	(3) lnRD	(4) CI	(5) lnRD	(6) CI	(7) lnRD	(8) CI
AI	0.042*	−11.031*	0.045	−19.393*	0.031	−3.619	0.103*	7.883
	(1.915)	(−1.871)	(1.512)	(−1.773)	(0.916)	(−0.493)	(1.785)	(0.497)
lnRD		−8.462***		−12.232**		−2.797		−18.821*
		(−2.732)		(−2.096)		(−0.627)		(−1.951)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	18,677	18,401	8,977	8,834	6,662	6,594	2,980	2,917
R^2	0.560	0.053	0.607	0.061	0.523	0.067	0.483	0.083

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses.

V. Heterogeneity analysis

Firm-level heterogeneity

Our results indicate that AI significantly reduces firms' carbon emission intensity, particularly in growth-stage firms. We explore the heterogeneity of this impact considering firm- and industry-level characteristics. Table 8 presents the regression results for the firm-level heterogeneity effects of AI on carbon emission intensity.

Ownership

The AI coefficient is significantly negative for state-owned enterprises (SOEs) but not for non-SOEs, with no significant effects across the lifecycle stages. This may reflect the fact that SOEs, which are supported by government funding and dual economic-social objectives, are willing to invest in AI for carbon reduction. In contrast, non-SOEs, which are driven by market competition and focus on short-term gains, are cautious about the substantial investments required to reduce emissions.

Firm size

The impact of AI on carbon emission intensity varies by firm size. Medium-sized firms exhibit a significantly negative AI coefficient, whereas small and large firms do not exhibit significantly positive coefficients. Moreover, AI reduces emissions primarily during the growth stage of medium and large firms, likely reflecting a balance between expansion and stability. Mature-stage firms have

Table 8. Firm-level heterogeneity results.

	(1) Full	(2) Growth	(3) Maturity	(4) Decline
Panel A: State-Owned Enterprises				
AI	−16.130**	−23.486	−8.498	−28.588
	(−2.065)	(−1.586)	(−0.863)	(−1.040)
Observations	8,586	3,574	3,447	1,517
R^2	0.067	0.071	0.080	0.096
Panel B: Non-State-Owned Enterprises				
AI	−9.092	−14.01	−0.572	−6.049
	(−1.413)	(−1.212)	(−0.074)	(−0.369)
Observations	16,165	7,952	5,407	2,754
R^2	0.060	0.070	0.055	0.102
Panel A: Small Firms				
AI	−0.710	−18.589	−102.190**	4.603
	(−0.035)	(−0.627)	(−2.549)	(0.081)
Observations	1,565	729	388	416
R^2	0.103	0.139	0.203	0.236
Panel B: Medium Firms				
AI	−42.865**	−62.295*	−3.948	−48.086
	(−2.365)	(−1.664)	(−0.178)	(−1.320)
Observations	5,032	2,309	1,610	1,070
R^2	0.058	0.095	0.074	0.136
Panel C: Large Firms				
AI	−7.647	−21.612**	3.758	0.142
	(−1.464)	(−2.232)	(0.565)	(0.009)
Observations	18,158	8,489	6,857	2,787
R^2	0.058	0.055	0.065	0.088

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses. All regressions have control variables, time fixed effects, and firm fixed effects.

established production systems that complicate AI integration, whereas small firms constrained by limited resources tend to focus on economic efficiency over costly environmental technology investments.

Industry-level heterogeneity

Table 9 presents the effects of AI from an industry-level perspective.

Table 9. Industry-level heterogeneity results.

	(1) Full Sample	(2) Growth	(3) Maturity	(4) Decline
Panel A: Manufacturing				
AI	−9.765*	−13.112	−4.866	−15.810
	(−1.847)	(−1.329)	(−0.778)	(−1.235)
Observations	20,004	9,370	7,174	3,377
R^2	0.053	0.060	0.064	0.081
Panel B: Non-Manufacturing				
AI	−10.579	−23.208	5.815	−88.478
	(−0.801)	(−1.007)	(0.328)	(−1.558)
Observations	4,751	2,157	1,681	896
R^2	0.081	0.089	0.074	0.155
Panel A: High-Pollution Industries				
AI	−21.435***	−33.590**	−12.257	−36.907
	(−2.655)	(−2.020)	(−1.433)	(−1.624)
Observations	8,734	3,965	3,543	1,199
R^2	0.054	0.063	0.065	0.086
Panel B: Low-Pollution Industries				
AI	−2.929	−5.547	3.491	−16.118
	(−0.466)	(−0.500)	(0.425)	(−0.950)
Observations	16,021	7,562	5,312	3,074
R^2	0.059	0.060	0.067	0.092
Panel A: High-Tech Industries				
AI	−8.929	−10.698	−6.344	−11.016
	(−1.498)	(−0.966)	(−0.856)	(−0.818)
Observations	15,793	7,572	5,521	2,639
R^2	0.056	0.061	0.060	0.112
Panel B: Non-High-Tech Industries				
AI	−15.474*	−28.104*	2.716	−46.358
	(−1.756)	(−1.697)	(0.262)	(−1.459)
Observations	8,934	3,941	3,325	1,630
R^2	0.056	0.055	0.074	0.100
Panel A: Labor-Intensive Industries				
AI	−12.549	−26.247	6.111	−26.119
	(−1.391)	(−1.414)	(0.539)	(−0.773)
Observations	5,825	2,547	2,320	926
R2	0.061	0.064	0.079	0.123
Panel B: Capital-Intensive Industries				
AI	−28.229**	−36.506*	−17.972	−40.080
	(−2.528)	(−1.725)	(−1.555)	(−0.948)
Observations	7,110	3,328	2,551	1,212
R2	0.054	0.053	0.082	0.088
Panel C: Technology-Intensive Industries				
AI	1.710	1.352	2.451	−2.748
	(0.252)	(0.109)	(0.272)	(−0.200)
Observations	11,818	5,650	3,984	2,135
R2	0.056	0.064	0.052	0.114

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; t-values in parentheses. All regressions have control variables, time fixed effects, and firm fixed effects.

Manufacturing versus non-manufacturing industries

The AI coefficient is significantly negative for manufacturing firms, whereas it is not for non-manufacturing firms. Manufacturing processes, such as raw material handling and assembly, offer scope for AI to optimize operations, reduce energy use, and curb emissions. Non-manufacturing firms generally have low energy consumption and emission intensity; therefore, AI has a small effect. These results align with those of C. Li et al. (2023) and explain the regional differences noted by Tao, Wang, and Zhai (2023), as areas with higher manufacturing shares show greater carbon reductions from AI adoption.

High-pollution versus low-pollution industries

For high-pollution industries, AI significantly reduces carbon emission intensity, whereas the effect is not significant for low-pollution industries. Across the lifecycle, this reduction appears mainly in the growth stage of high-pollution industries, which face strict regulations and high-emission processes. Low-pollution industries experience less regulatory pressure and have lower emissions, thus exhibiting a weaker AI effect. These findings provide micro-level evidence consistent with those of Yu et al. (2023) and C. Li et al. (2023), who report AI's carbon-reducing impact at the industry level.

High-tech versus non-high-tech industries

In non-high-tech industries (Peng and Mao 2017), AI significantly reduces carbon intensity; however, no similar effect is observed in high-tech industries. This reduction during the growth stage in non-high-tech sectors is likely because these firms rely on traditional energy, which can be optimized by AI, and have capital for AI investments. High-tech firms often operate with low emissions or use advanced low-carbon technologies, allowing little room for AI-driven cuts. This finding differs from that of L. Liu et al. (2021), whose 2006–2016 sample reflected AI as automation. By extending the sample to 2021, this study captures newer AI technologies, such as deep learning and big data, that may affect post-2016 high-tech firms differently.

Factor intensity

Dividing the sample by factor intensity (Dong and Guo 2021) reveals that AI significantly lowers carbon emission intensity in capital-intensive industries, particularly during the growth stage. These firms rely on capital equipment, and AI allows precise resource allocation and energy use. During their growth, these firms have resources to invest in AI and environmental technologies. In contrast, labour-intensive firms have a limited capacity to reduce emissions, and technology-intensive firms that are already heavily automated gain less from AI implementation.

VI. Discussion

The results reveal that AI significantly reduces corporate carbon emission intensity. The reduction is particularly pronounced during the growth stage, while the impact on mature- and decline-stage enterprises is insignificant. AI reduces corporate carbon emission intensity by improving productivity and promoting innovation, manifested mainly during the growth and decline stages, respectively. The impact of AI on corporate carbon emission intensity varies based on firm and industry attributes. AI use significantly reduces carbon emission intensity in state-owned enterprises; growth-stage medium and large enterprises; manufacturing enterprises; and growth-stage enterprises in heavily polluting, non-high-tech, and capital-intensive industries.

In the context of sustainable business models, the resource-based perspective posits that firms can achieve competitive advantages by leveraging sustainable resources and capabilities (Huang and Zhou 2025). AI serves as a strategic resource and dynamic capability that enhances operational efficiency and environmental performance according to the Natural-Resource-Based View (Alkaraan et al. 2024). AI enables firms to optimize production processes, reduce waste, and improve energy efficiency, thereby lowering carbon emissions. For instance, AI-driven predictive maintenance can anticipate equipment failures and reduce downtime and energy consumption. In addition, AI algorithms can optimize supply chain logistics, leading to decreased fuel usage and associated emissions.

Furthermore, absorptive capacity, that is, the ability to recognize, assimilate, and apply new information, is critical to AI's effectiveness in reducing carbon emissions over a firm's lifecycle. In the start-up phase, firms typically have limited resources and informal structures, resulting in low absorptive capacity (Phelps, Adams, and Bessant 2007) and challenges in adopting AI to achieve carbon reduction. External partnerships can help develop the necessary capabilities. As firms expand, they establish formal processes that enhance their capacity to integrate AI effectively, leading to improved energy efficiency and lower emissions. This is consistent with findings by C. Wang, Zhang, and Teng (2023) on green absorptive capacity and innovation. In contrast, decline-stage firms often exhibit rigid structures and diminished absorptive capacity, limiting AI adoption. Revitalization should focus on boosting absorptive capacity by fostering openness to external knowledge and restructuring processes, thereby enabling the reintegration of AI solutions for carbon reduction and facilitating the return on growth.

The recent literature supports these interpretations. For instance, studies show that the AI-empowered technologies significantly reduce carbon dioxide emissions, particularly in the early stages of adoption (Kuang et al. 2024). This reduction is attributed to the improved resource utilization and absorptive capacity of AI. However, the environmental costs associated with AI implementation at an aggregate level must be acknowledged. Training AI models can be energy-intensive, contributing to increased carbon emissions. For instance, training large AI models consumes substantial amounts of energy, leading to a significant carbon footprint (Alzoubi and Mishra 2024). Therefore, firms must balance the benefits of AI adoption with strategies to mitigate its environmental impacts, such as utilizing energy-efficient hardware and sourcing renewable energy for data centres.

We derive several policy implications based on the results of this study. First, considering the significant negative relationship between AI adoption and carbon emission intensity, policymakers should actively promote AI-driven green technologies. Incentives such as tax reductions, R&D

subsidies, and financial support should be provided to encourage firms to integrate AI into their production processes. Firms in high-carbon industries should focus on overcoming the initial adoption barriers.

Moreover, as AI adoption has the strongest carbon reduction effect on growth-stage firms, with negligible effects on mature- and decline-stage firms, policymakers should develop differentiated AI promotion strategies. For growth-stage firms, AI investments should be encouraged through targeted financial incentives and training programmes to maximize productivity gains and reduce emissions. For mature-stage firms, policymakers should support AI-driven business model innovations that enhance environmental efficiency. For decline-stage firms, AI's role in fostering innovation should be assisted by offering transformation-oriented grants and industry-specific guidance to help firms reorient their strategies towards sustainable operations.

As AI primarily reduces carbon emissions through productivity improvements in growth-stage firms and innovation in decline-stage firms, government support should promote AI-driven operational efficiency by facilitating access to digital infrastructures, cloud computing, and AI-enabled energy management systems. In addition, policies should strengthen R&D investment incentives to support innovation in firms undergoing restructuring or seeking to transition towards productive models (Foreman-Peck and Zhou 2022, 2023).

Furthermore, the carbon reduction benefits of AI are the most pronounced in state-owned, medium-sized, manufacturing, high-pollution, non-high-tech, and capital-intensive firms. Therefore, policies should prioritize AI deployment in manufacturing and high-emission industries by offering sector-specific incentives and environmental compliance benefits. Moreover, policies should encourage state-owned enterprises to adopt AI as role models in sustainable corporate practices. Governments should provide tailored AI adoption support for capital-intensive industries, in which AI can significantly optimize energy and resource use.

VII. Conclusion

This study indicates that that AI can reduce corporate carbon emission intensity. Our findings contribute to the growing literature on digital technologies and environmental sustainability by introducing the firm lifecycle dimension. While previous research has mainly adopted a static perspective (Zhang and Yu 2024), this study is among the first to systematically examine AI's role in carbon reduction through the lens of the firm lifecycle theory. Furthermore, by distinguishing among growth-, mature-, and decline-stage firms, this study moves beyond static analyses to develop a dynamic framework that captures the heterogeneous effects of AI adoption on corporate carbon emission intensity and provides a nuanced understanding of AI implementation among firms with varying operational strategies. Moreover, this study highlights the importance of firm and industry characteristics in determining the effectiveness of AI implementation. The observed heterogeneity across firm size, ownership structure, and industry type suggests that AI's impact is non-uniform. These findings can be understood using two well-established theoretical paradigms: resource-based view and absorptive capacity. In addition, this study identifies two distinct mechanisms through which AI reduces carbon emission intensity: improving productivity, which particularly benefits growth-stage firms, and fostering innovation, which benefits decline-stage firms. This refinement helps resolve the divergent results at the industrial and regional levels in previous studies (Chen et al. 2022; Tao, Wang, and Zhai 2023; Yu et al. 2023). Firm-level evidence also provides practical insights into the development of targeted AI application strategies for firms across different lifecycles.

Although this study provides a comprehensive analysis, future research should address several limitations. First, future studies should examine the long-term effect of AI implementation on corporate sustainability to provide deeper insight into the persistence and dynamics of AI-induced carbon reduction. Second, integrating micro-level data on AI technologies, such as machine learning models and automation systems, could refine our understanding of AI's specific role of AI in emission management. Third, cross-country comparisons could shed light on the roles of regulatory frameworks and market dynamics in the environmental effects of AI, thereby offering global policy recommendations.

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Data availability statement

Data available on request from the authors.

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