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How does artificial intelligence impact corporate ESG performance? The catching–up effect of digital technological innovation

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ABSTRACT

Against the backdrop of the deep integration between the digital economy and corporate sustainable development, this study uses the national New Generation Artificial Intelligence Innovation and Development Pilot Zone (AI_IDPZ) policy as a quasi-natural experiment. Based on data from Chinese A-share listed companies from 2009 to 2023, this study employs a difference-in-differences model to empirically examine the impact of artificial intelligence (AI) on corporate environmental, social, and governance (ESG) performance and its underlying mechanisms while revealing the catching-up effect of digital technological innovation through heterogeneity analysis. Results show that the AI_IDPZ policy has a significantly positive impact on corporate ESG performance. The policy systematically enhances firms' ESG through multiple pathways, including digital transformation, green innovation, and corporate social responsibility information disclosure. This policy effect manifests as a "catching-up effect" of digital technological innovation for ESG laggards in regions with lower digital economic development levels and firms with weaker digital transformation foundations. Specifically, entities with initially weaker technological bases can more effectively use AI technology to narrow their ESG gap with leading counterparts and achieve leapfrog improvements in sustainable development performance through policy empowerment. This catching-up effect is driven by technological innovation and market participation. By expanding the technological innovation perspective in ESG research, this study provides a theoretical foundation for policymakers to optimize region-specific support strategies and for corporate managers to design digital ESG improvement pathways. It also offers new empirical evidence on how technological innovation can drive corporate sustainable development in the digital economy era.

Introduction

In the context of the accelerating global integration between green and digital development, firms are increasingly confronted with the strategic challenge of a twin transition, namely, the need to achieve synergy between green transformation and digitalization (Fouquet & Hippe, 2022; Müller et al., 2024; Rehman et al., 2023; Tabares et al., 2025; Hofmann Trevisan et al., 2024). Artificial intelligence (AI), as a representative of digital technological advancement, is rapidly reshaping firms' production processes, governance structures, and pathways toward sustainable development (Agrawal et al., 2019; Kulkov et al., 2024; Xie & Wu, 2025). Simultaneously, environmental, social, and governance (ESG) performance has become a critical benchmark for assessing firms' long-term value, risk management capacity, and sustainability orientation, attracting widespread attention from policymakers, investors, and scholars (James, 2023; Seow, 2024; Waldau, 2024).

Within this evolving landscape, recent studies have examined the link between AI and corporate ESG performance. For instance, Li et al. (2025) and Zhang and Yang (2024) find that AI adoption enhances environmental and social outcomes. Chen and Zhang (2025) emphasize the importance of internal control systems and external information

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environments in shaping AI–ESG transmission mechanisms. Zhou et al. (2025) show that AI improves ESG outcomes primarily through enhanced information governance. Xiao and Xiao (2025) further demonstrate that AI-driven ESG practices significantly enhance the sustainability performance of central state-owned enterprises. While these studies offer valuable empirical insights, several gaps remain: (1) most focus on AI usage rather than policy-driven adoption and thus lack an institutional policy lens; (2) current research disproportionately emphasizes large firms or specific sectors, with insufficient exploration of AI's role in resource-constrained or digitally lagging enterprises; and (3) the theoretical discussion on the "catching-up effect" of digital technologies on ESG upgrading is limited.

To address these gaps, this study constructs an integrated theoretical framework grounded in twin transition theory and ESG theory to systematically explore how AI policy promotes corporate ESG performance through digital transformation. Twin transition theory argues that green and digital transitions are mutually reinforcing rather than independent trajectories. At the firm level, this synergy relies on the embedded support of digital technologies for green strategies, including smart resource allocation, information transparency, and process greening (Pricopoaia et al., 2025). As a core enabler of digital transformation, AI has a strong potential to drive "green–digital synergy, especially in firms with weak digital infrastructure, where AI policies can facilitate leapfrogging in ESG performance through institutionalized technological empowerment. Simultaneously, ESG theory highlights the strategic value of non-financial performance, emphasizing environmental management, social responsibility, and governance quality. AI enhances data processing and disclosure capacity, thereby improving firms' ESG outcomes across all three dimensions. By bridging these two theoretical perspectives, this study elucidates the mechanisms through which AI policy integrates with corporate green governance, activates social responsibility, and enhances governance transparency, thereby clarifying the logic and boundary conditions of AI-driven sustainable transformation.

Building on this framework, we adopt a quasi-natural experimental design by exploiting the national New Generation Artificial Intelligence Innovation and Development Pilot Zone (AI_IDPZ) policy and construct a difference-in-differences (DID) model using panel data on Chinese A-share listed firms from 2009 to 2023. We empirically examine the impact of AI policy on ESG performance, explore the underlying mechanisms, and analyze heterogeneity effects. Focusing on Chinese firms is meaningful both empirically and theoretically. First, China is among the world's most active digital economies, with its digital economy reaching RMB 53.9 trillion in 2023, accounting for 42.8 % of its GDP (China Academy of Information and Communications Technology, 2024). Thus, it offers a rich empirical setting for analyzing the synergy between AI and sustainable development and providing policy insights for digital latecomer economies. Second, as the world's largest developing country, China is actively promoting digitally empowered green transformation, serving as a globally significant case for the twin transition. Thus, studying Chinese firms contributes to identifying effective ESG-enhancing mechanisms in developing economies under resource constraints and enriches the international discourse on twin transition theory and policy frameworks.

Our empirical findings indicate that the AI policy significantly enhances a firm's ESG performance, particularly in terms of environmental management, social engagement, and governance transparency. Furthermore, the effects are more pronounced among firms and regions with weaker digital infrastructure, validating the role of the "digital catching-up effect" in driving sustainable corporate transformation. This study contributes to the literature in three key ways: (1) it addresses the insufficient theoretical and empirical linkage between AI and corporate sustainability, introducing a digital technology dimension to ESG research; (2) it proposes and validates the mechanism of "digital catching-up" within the context of corporate governance, thereby extending the applicability of twin transition theory to emerging economies; and (3) it provides evidence-based implications for policymakers to design differentiated AI empowerment strategies and for firms to construct AI-enabled ESG transition pathways.

Theoretical foundation and research hypotheses

Guided by sustainable development goals, AI may systematically enhance corporate ESG performance through digital transformation-driven restructuring, green innovation empowerment, and strengthened corporate social responsibility (CSR) information disclosure by reshaping firms' resource allocation logic and value creation paradigms.

From the perspective of technology–organization fit theory (Tushman & Nadler, 1978), AI-driven digital transformation first reconstructs firms' resource allocation paradigms through technological empowerment. Its algorithm optimization and data modeling capabilities transcend the resource constraint boundaries of traditional production functions by internalizing environmental factors as dynamic decision variables (Kaggwa et al., 2024; Kalusivalingam et al., 2020). According to dynamic optimization theory (Bellman, 1966), real-time production scheduling and energy management feedback mechanisms drive enterprises from fragmented end-of-pipe governance to life cycle environmental management. This technological embedding further triggers process reengineering; for example, AI-generated carbon emission prediction models and circular economy resource allocation algorithms align with the core logic of Porter's hypothesis (Porter & van der Linde, 1995) by internalizing negative environmental externalities, where environmental management capabilities transform into differentiated competitive advantages. Institutionally, AI's natural language processing standardizes ESG information disclosure frameworks, satisfying organizations' pursuit of external legitimacy under institutional theory (DiMaggio & Powell, 1983) and promoting the evolution of governance structures toward data-driven institutionalization.

AI's promotion of corporate green innovation can be interpreted within the analytical framework of ecological modernization theory (Mol et al., 2020), which emphasizes the co-evolution of technological innovation and environmental sustainability. With data-driven innovation as its core engine, AI uses machine learning models to analyze massive amounts of environmental data, identify critical pathways for green technology R&D, and reduce innovation trial-and-error costs (Chen et al., 2023). In application scenarios, AI algorithms optimize clean energy production processes (e.g., improving the energy efficiency of photovoltaic power plants) and drive breakthroughs in waste recycling technologies, shifting enterprises from passive pollution control to proactive ecological technology innovation (Mellit et al., 2009; Tutore et al., 2024). More importantly, AI-supported blockchain technology constructs a collaborative governance system for green supply chains, thus promoting low-carbon transformation at the industrial cluster level through the real-time sharing of upstream and downstream environmental data and smart contract execution and amplifying the multiplicative effect of the "technology−environment" synergy (Charles et al., 2023; Yin et al., 2023).

In the CSR information disclosure dimension, AI reconstructs the interaction model between enterprises and multiple stakeholders using the core logic of stakeholder theory (Freeman, 2010), which emphasizes balancing the needs of diverse stakeholders. AI's transparency-enhancing technologies provide technological solutions (Ezzi et al., 2023; Sætra, 2023). Blockchain's distributed ledger technology establishes a traceable supply chain governance system, converting social dimension indicators such as labor standards and product quality into tamper-proof digital signals to address information asymmetry in traditional disclosure models (Almadadha, 2024; Kummer et al., 2020). Natural language processing automates the analysis of unstructured corporate data to generate standardized ESG performance evaluation models, enhancing the comparability and credibility of disclosed content (Zhao et al., 2022). AI's real-time monitoring and early risk warning functions further reduce principal–agent costs and build dynamic response mechanisms in compliance reviews to ensure alignment between CSR practices and governance goals (Wall, 2021).

The synergistic effects of these three mechanisms reflect the construction of firms' dynamic capabilities (Teece et al., 1997), emphasizing that organizations form adaptive competitiveness by integrating external technologies and internal resources. AI serves as a core enabling tool for this process. This capability restructuring improves the measurability and operability of ESG practices. It embeds sustainable development concepts into corporate DNA through technological embedding, thereby facilitating a paradigm shift from passive compliance to proactive innovation. Thus, we propose Hypothesis 1.

Hypothesis 1. AI systematically enhances corporate ESG performance through digital transformation-driven restructuring, green innovation empowerment, and strengthened CSR information disclosure.

The positive impact of AI on corporate ESG performance may manifest as distinct digital technology catching-up dynamics, particularly evident in enterprises in regions characterized by less developed digital economies and those demonstrating lower levels of internal digital transformation maturity.

From the perspective of technological catch-up theory (Abramovitz, 1986), enterprises in regions with low digital economic levels often face technological backwardness and information asymmetry in traditional ESG practices. AI technology provides these enterprises with opportunities for "leapfrog development," that is, they can directly adopt advanced ESG management tools to narrow the gap with industry leaders rapidly. For example, Song et al. (2025) empirically showed that driven by environmental regulation policies, digital transformation significantly improve companies' ESG performance, with particularly prominent effects in regions with weak digital infrastructure and low corporate digitalization levels. This finding aligns with the core argument of Abramovitz (1986) that technological followers can achieve rapid development through technology absorption and imitation and that AI's modular solutions lower the adoption threshold for ESG technologies.

Digital divide theory further clarifies the internal mechanism: low-digitalization enterprises typically face issues such as insufficient internal data processing capabilities and limited access to ESG-related information, leading to poor ESG disclosure quality and ineffective risk management. AI's data analysis capabilities enable these enterprises to efficiently collect and analyze unstructured ESG data, thereby enhancing information transparency and decision accuracy.

Dynamic capabilities theory (Teece et al., 1997) explains how AI reshapes firms' ESG management capabilities. For low-digitalization enterprises, AI also fosters the evolution of adaptive capacities, including real-time environmental risk monitoring, early warning systems, and stakeholder engagement frameworks, thereby enabling organizations to adapt promptly to shifts in ESG regulatory landscapes (Rane et al., 2024). For example, AI's real-time monitoring models help enterprises identify ESG risks and proactively adjust strategies to enhance governance efficiency. This process aligns with the view of Teece et al. (1997) that dynamic capabilities allow enterprises to integrate external technologies and internal resources to adapt to environmental changes.

Empirical research further supports the heterogeneity of AI's impact on ESG. Xie and Wu (2025) found that AI's promoting effect on ESG performance is more significant in competitive industries and technology-intensive enterprises as they face more substantial pressures for technology adoption; additionally, this effect is more prominent in central and eastern China than in western and northeastern regions, reflecting the moderating role of regional digital infrastructure.

In summary, AI's ESG-promoting effect in low-digitalization enterprises reflects a technology catching-up effect driven by three mechanisms: (1) "leapfrog development" through technology adoption, (2) "information equity" facilitated by data analysis, and (3) "capability building" driven by dynamic adaptation. This effect improves firms' ESG performance and supports sustainable development in regions that lag in the digital economy. Against this theoretical and empirical backdrop, we advance Hypothesis 2 as follows.

Hypothesis 2. The ESG-promoting effect of AI on low-digitalization enterprises reflects the catching-up effect of digital technological innovation.

The positive impact of AI on corporate ESG performance is likely to be more pronounced in high-technology sector firms and non-state-owned enterprises (SOEs), a pattern that fundamentally embodies the underlying mechanism of digital technology catching-up dynamics driven jointly by technological innovation impetus and market engagement forces.

The high-intensity demand for technological innovation and rapid iteration in high-tech industries endow enterprises with inherently high absorption and transformation efficiency for AI technology. According to technological catch-up theory (Abramovitz, 1986), high-tech enterprises face fierce global competition and technological barriers, requiring their ESG practices to simultaneously address complex issues such as environmental technology innovation, social-dimensional technological ethics, and governance-level innovation compliance. AI technology helps these enterprises break through the linear model of traditional ESG management by empowering R&D processes, supply chain management, and governance decision-making, forming a spiral enhancement effect of "technological innovation−ESG performance" (Lu et al., 2025). For example, the early adoption of AI in the semiconductor industry not only improves energy efficiency in production (environmental dimension) but also constructs a technological ethics governance system through algorithm transparency frameworks (governance dimension). Such impact aligns with the core logic of Teece et al. (1997) that dynamic capabilities enhance organizational adaptability by integrating technological resources.

The market-oriented nature of non-SOEs strengthens AI's promotional effect on ESG. Based on institutional environment theory (North, 1990), non-SOEs face more direct market competition pressures and resource constraints, with decision-making mechanisms being more dependent on efficiency-oriented technological investments. As a key tool for reducing information asymmetry and improving stakeholder response speed, AI more easily breaks through the constraints of hierarchical structures in non-SOEs and is quickly integrated into ESG management processes (Sun & Mohd Saat, 2023; Wang et al., 2023). For instance, non-SOEs using AI-driven supply chain ESG risk assessment systems can respond more flexibly to consumer demands for sustainable products. This agility aligns with the positive cycle of "technology application−market feedback" under market participation.

Meanwhile, agency theory notes that non-SOEs typically have more dispersed ownership structures, with management facing the substantial dual constraints of market value management and CSR. AI's ESG data visualization functions effectively reduce agency costs and enhance external investor confidence.

These industry and ownership differences collectively reveal the formation path of the catching-up effect of digital technological innovation. Specifically, in high-tech industries, AI breaks through ESG practice bottlenecks through the "enabling effect" of technological innovation. This capability is consistent with the hypothesis of Abramovitz (1986) that more significant technological gaps imply higher catch-up potential. Meanwhile, in non-SOEs, the "selection effect" driven by market competition accelerates the transformation of AI technology into ESG management capabilities, reflecting the moderating role of institutional environments on technology application efficiency. The superposition of these dual mechanisms makes AI a tool for technological innovation and a carrier of dynamic capabilities for enterprises to adapt to market environments and build sustainable competitive advantages. Thus, we propose Hypothesis 3.

Hypothesis 3. Technological innovation and market participation form the catching-up effect of digital technological innovation on AI's ESG-promoting effect.

Fig. 1 presents the main research content and ideas of this study.

Research design

Model specification

We employ a DID model to identify the causal impact of the AI_IDPZ policy on corporate ESG performance. Widely used in policy evaluation and quasi-natural experimental settings, the DID approach enables the estimation of treatment effects by controlling for unobserved time-invariant heterogeneity and comparing changes in outcomes between treatment and control groups before and after policy implementation (Bertrand et al., 2004).

Unlike ordinary least squares (OLS) or fixed effects models, the DID framework does not rely on the assumption of a random assignment of a treatment variable. Instead, it is grounded in the parallel trends assumption, that is, without policy intervention, the treatment and control groups would exhibit similar trends in the outcome variable. We empirically test this assumption using both graphical and statistical methods in the subsequent section. The results confirm that the pretreatment trends are sufficiently parallel, thereby strengthening the causal validity of our estimation. Compared with other econometric techniques such as instrumental variables or regression discontinuity designs, the DID approach is particularly well-suited for analyzing macro-level policy shocks across a large sample, and it circumvents the identification challenges associated with finding valid exogenous instruments.

The establishment of the AI_IDPZ policy provides a well-defined policy intervention with a clear implementation timeline and city-level coverage, satisfying the criteria for a quasi-natural experiment. The DID approach aligns with the theoretical logic of institutional change and policy shocks, and its structure is consistent with the counterfactual inference framework (Rubin, 1974), whereby the performance of untreated firms serves as a benchmark for estimating the net effect of the policy. To further strengthen the robustness of our identification strategy, we supplement the baseline DID model with additional empirical checks, including propensity score matching (PSM)−DID, placebo tests, and the exclusion of potentially confounding policy interventions. These efforts are aimed at enhancing the credibility of our causal inference and the robustness of our empirical findings. The model is constructed as follows:

$$ESG_{i,t} = \alpha + \beta \times DID_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

The dependent variable, $ESG_{i,t}$, denotes the ESG performance of firm i in year t, which captures the firm's overall achievements in environmental management, social responsibility, and corporate governance.

The core explanatory variable, $DID_{i,t}$, is an interaction term defined as $treat_i \times post_t$. The variable $treat_i$ is a binary indicator equal to 1 if the firm is located in a city designated as part of the AI_IDPZ and 0 otherwise. The variable $post_t$ is a time dummy equal to 1 for years following policy implementation and 0 otherwise. This construction exploits both cross-sectional (across cities) and temporal (over time) variations in the AI_IDPZ rollout, thus providing a quasi-natural experimental setting to identify the policy's net effect on corporate ESG outcomes. The AI_IDPZ policy was established in three batches (2019, 2020, and 2021) covering 18 cities. In our study, firms are matched to policy exposure using their registered locations.

$X_{i,t}$ represents the control variables, covering both the firm and city levels. To enhance estimation accuracy and address potential confounding factors, we incorporate a comprehensive set of firm-level control variables, drawing from Song et al. (2025). These variables include firm size (*Size*), revenue growth rate (*Growth,* the unit is %), ownership concentration (*Top10*), fixed asset ratio (*FAratio*), industry concentration (*HHI*), leverage ratio (*Lev*), and book-to-market ratio (*BM*). These variables control for factors related to firm size, growth potential, governance structure, capital structure, industry competition,

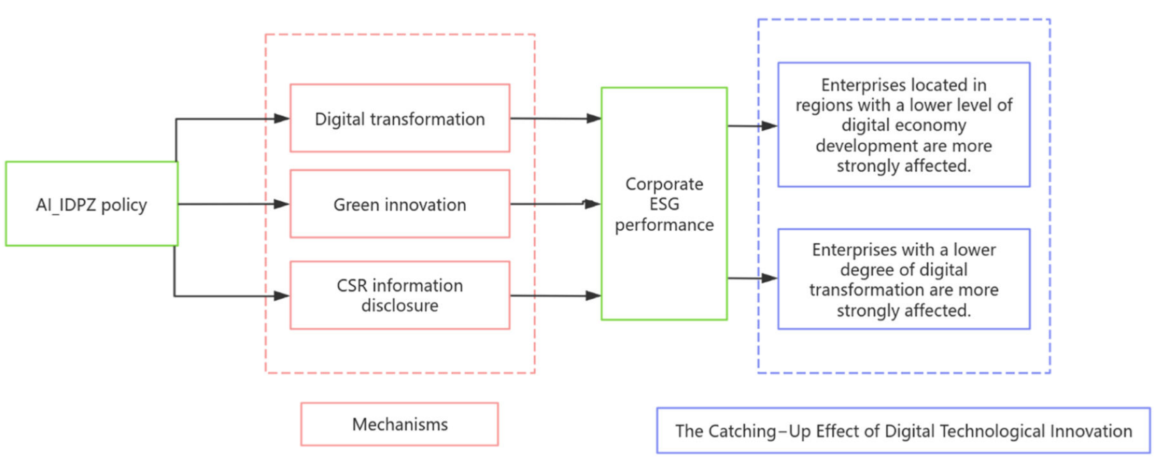

Fig. 1. Main research content and ideas.

and valuation, all of which may influence ESG performance. At the city level, we include per-capita GDP (*GDPpc*) and the share of secondary and tertiary industry value-added in GDP (*Instruct*) to capture regional economic development and industrial upgrading, respectively.

To mitigate omitted variable bias, we introduce firm fixed effects (μ_i) to control for unobserved, time-invariant firm-specific factors, such as corporate culture or long-standing governance practices. Year fixed effects (λ_t) are included to absorb macroeconomic shocks or institutional changes that uniformly affect all firms, such as regulatory shifts or global ESG reporting trends. Given that the policy is assigned at the city level and firms within a city may be subject to correlated shocks, we cluster standard errors (ε_{it}) at the city level to ensure a robust statistical inference.

The identification strategy is grounded in the counterfactual inference framework and established policy evaluation theory (Angrist & Pischke, 2009; Rubin, 1974). The DID estimator isolates the policy's causal effect (β) by comparing changes in ESG performance over time between treated and control firms. To strengthen the robustness and credibility of the findings, we further implement a series of diagnostic tests, including parallel trends analysis, placebo tests, and the combined PSM–DID approach.

Data and sample construction

This study conducts an empirical analysis using panel data from Chinese A-share listed firms for the period 2009–2023. The initial year, 2009, is selected based on data availability for the dependent variable of corporate ESG performance. The ESG data are primarily drawn from major third-party ESG rating databases, which began the systematic disclosure and evaluation of A-share listed firms in 2009, providing relatively comprehensive coverage. The end year, 2023, reflects the latest complete data available at the time of this study. This time window also captures the announcement and multistage implementation of the AI_IDPZ policy, enabling us to identify its dynamic effects on ESG performance.

Focusing on Chinese A-share listed companies offers both theoretical and practical advantages. On the one hand, these firms exhibit greater consistency in information disclosure, governance standards, and responsiveness to policy, thereby enhancing the precision and comparability of model identification. On the other hand, A-share listed companies span a wide range of regions and industries, making them well-suited to reflect the broader trajectory of corporate digital and sustainable transformation in China. Moreover, firm-level heterogeneity analyses, such as differences in digital readiness and industry attributes, are based on this large sample, improving the generalizability of the findings and the explanatory power of the resulting policy implications.

City-level data, including *GDPpc* and *Indstruct*, are primarily obtained from the China Urban Statistical Yearbook, China Statistical Yearbook, and annual statistical reports published by provincial and municipal statistics bureaus.

Firm-level data are extracted from authoritative financial databases such as the China Stock Market & Accounting Research (CSMAR) and Wind databases by matching annual financial reports and ownership structure data. Corporate ESG performance is measured using standardized ratings from the Huazheng ESG database, a professional rating system widely adopted in empirical studies on Chinese firms (Song et al., 2025; Xiao & Xiao, 2025). Compared with international ESG rating systems such as MSCI ESG and Refinitiv ESG, the Huazheng framework demonstrates a general alignment in its evaluation structure, focusing on three core dimensions: environmental (E), social (S), and corporate governance (G). The content is largely comparable across systems, covering key areas such as carbon emissions management, employee rights protection, and disclosure practices.

However, several key differences are noteworthy. First, the weighting schemes and emphasis vary. Huazheng ESG places greater emphasis on alignment with China's regulatory and policy priorities, such as the "dual carbon" goals and green finance initiatives, assigning more weight to regulatory compliance and pollution control under the environmental dimension. By contrast, international systems such as MSCI primarily focus on sustainability risk identification and financial materiality from a global investor perspective. Second, the data sources differ significantly. Huazheng relies on Chinese-language annual reports, official disclosures, and CSR reports that are processed using local natural language processing algorithms, whereas international systems often incorporate English-language databases, media sentiment monitoring, and third-party verification. Third, the application contexts diverge. International ESG ratings are designed for cross-country investment analysis, whereas Huazheng is more tailored to capturing Chinese firms' actual ESG practices and policy responsiveness within a localized regulatory environment. Given that this study focuses on Chinese A-share listed firms, Huazheng ESG ratings offer stronger empirical relevance and contextual fit in terms of policy alignment, data availability, and institutional consistency, thereby enhancing the explanatory power and real-world applicability of our analysis.

Policy data regarding the AI_IDPZ, including the list of pilot zones and policy implementation timelines, are determined based on official documents issued by the State Council and Ministry of Science and Technology. The first batch of pilot zones was launched in 2019; the cities covered by subsequent batches and their effective years are verified using publicly available information on government websites. Accordingly, the treatment dummy variable $treat_i$ (1 for firms in pilot cities, 0 otherwise) and the policy timing dummy variable $post_t$ (1 for the policy year and subsequent years, 0 otherwise) are constructed, with their interactions forming the core explanatory variable *DID*.

The mechanism variables include digital transformation (*DIGI_text*), green innovation (*Green_innov*), and corporate social responsibility disclosure (*CSR*). The digital transformation index, *DIGI_text*, is constructed using a textual analysis approach following the method proposed by Zhao et al. (2021), which quantifies the frequency of keywords related to digital transformation. The construction process is based on four key dimensions: digital technology application, internet-based business models, intelligent manufacturing, and modern information systems. Each dimension comprises several diagnostic keywords related to digital transformation. The complete list of these keywords is shown in Fig. 2. We calculate the frequency of keyword appearances in each of the four dimensions, normalize the word frequency data, and apply the entropy method to determine the weight of each dimension. The final *DIGI_text* score reflects a weighted composite index that represents a firm's degree of digital transformation.

Green_innov is measured by the ratio of green patent applications to the total number of patent applications, capturing the extent of environmentally oriented technological efforts by the firm. The *CSR* variable is constructed based on the widely adopted approach in the existing literature (Chen et al., 2018; Pan et al., 2018; Yuan et al., 2022) and using the CSR index provided by the CSMAR database. This index evaluates firms across eight dimensions: employee welfare, environmental protection, workplace safety, supplier protection, shareholder protection, customer protection, creditor protection, and CSR system development. For each subcategory, a firm receives a score of 1 if it exhibits outstanding performance and 0 otherwise. The total CSR score is the sum of the points across all eight subcategories, ranging from 0 to 8.

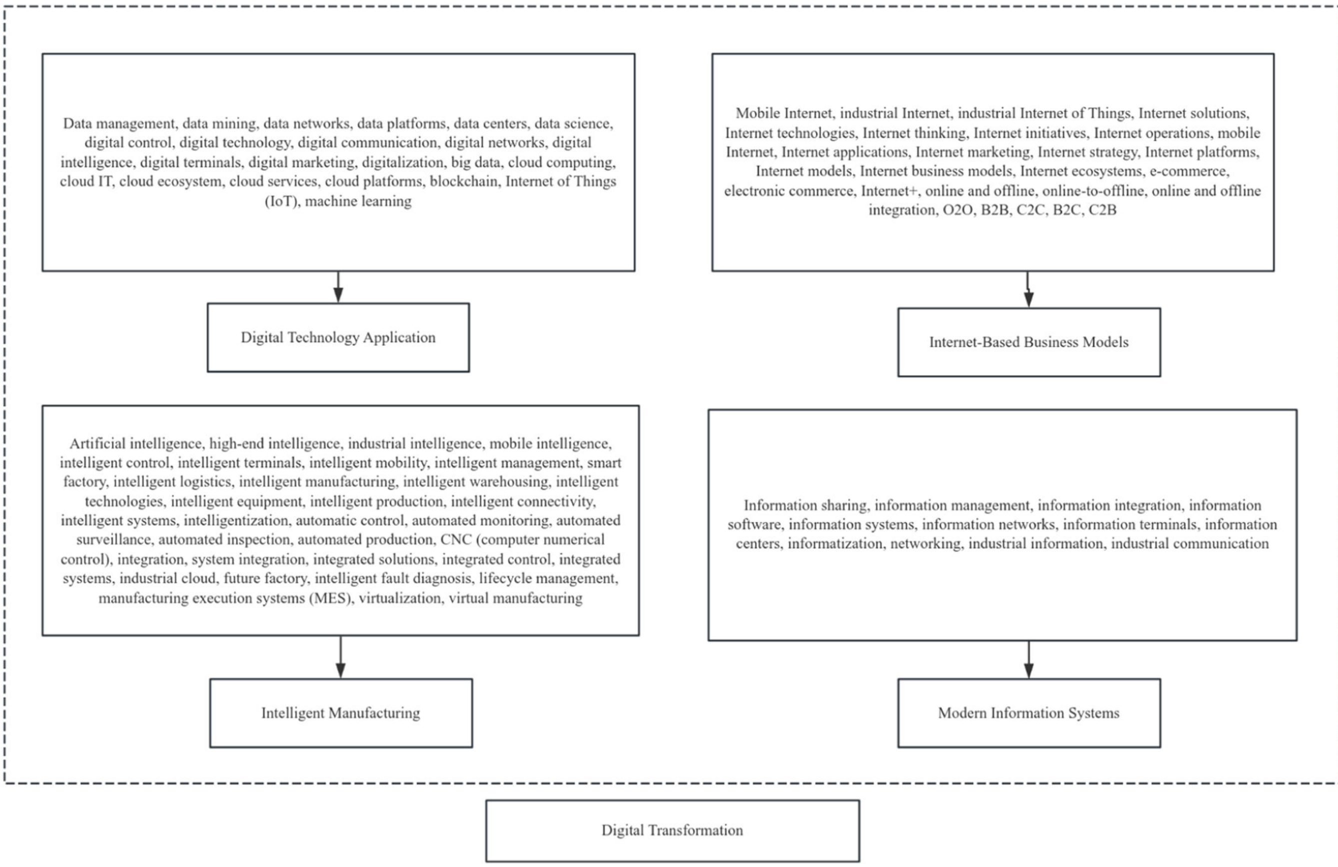

Fig. 2. Keyword list for constructing the enterprise digital transformation index.

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
ESG	36,829	4.1261	1.0000	1.0000	8.0000
DID	36,829	0.2349	0.4239	0	1.0000
Size	36,829	22.2196	1.4062	15.7152	28.6969
Growth	36,829	3.0351	312.0971	−41.5760	59,411.5500
Top10	36,829	58.1915	15.7074	1.3103	101.1600
FAratio	36,829	0.2015	0.1622	0	0.9709
HHI	36,829	0.2023	0.1845	0.0399	1.0000
Lev	36,829	0.4431	0.9998	0.0071	178.3455
BM	36,829	0.6207	0.2554	0.0057	1.6433
GDPpc	36,829	11.4544	0.5435	8.5993	12.4864
Instruct	36,829	95.8863	4.8152	51.4800	99.9700
DIGI_text	36,829	0.0155	0.0270	0	0.3918
Green_innov	36,829	0.0488	0.1448	0	1.0000
CSR	36,829	4.6085	2.7394	0	8.0000

Table 1 presents the descriptive statistics for these variables.

Empirical analysis

Baseline regression

Table 2 presents the baseline regression results. In Column (1), without any control variables, the *DID* coefficient is 0.1768, which is significant at the 1 % level. After adding the firm-level control variables in Column (2), the *DID* coefficient slightly decreases to 0.1679 but remains significant at the 1 % level, with narrower standard errors. In Column (3), which includes both the firm- and city-level control

Table 2
Baseline regression results.

Variable	(1) *ESG*	(2) *ESG*	(3) *ESG*
DID	0.1768***	0.1679***	0.1678***
	(0.0311)	(0.0286)	(0.0287)
Size		0.1550***	0.1545***
		(0.0138)	(0.0138)
Growth		−0.0000***	−0.0000***
		(0.0000)	(0.0000)
Top10		0.0046***	0.0046***
		(0.0009)	(0.0009)
FAratio		−0.3028***	−0.3021***
		(0.1021)	(0.1020)
HHI		−0.0133	−0.0133
		(0.0658)	(0.0661)
Lev		−0.0315	−0.0315
		(0.0234)	(0.0235)
BM		0.1682***	0.1698***
		(0.0500)	(0.0501)
GDPpc			0.0016
			(0.0636)
Instruct			0.0050
			(0.0067)
Constant	4.0845***	0.3493	−0.1379
	(0.0074)	(0.2874)	(0.6739)
Firm fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	36,829	36,829	36,829
R-squared	0.5125	0.5230	0.5230

Note: ***, **, and * represent significance at the 1 %, 5 %, and 10 % levels, respectively. The numbers in parentheses are robust standard errors clustered at the city level. The same note applies to the following table.

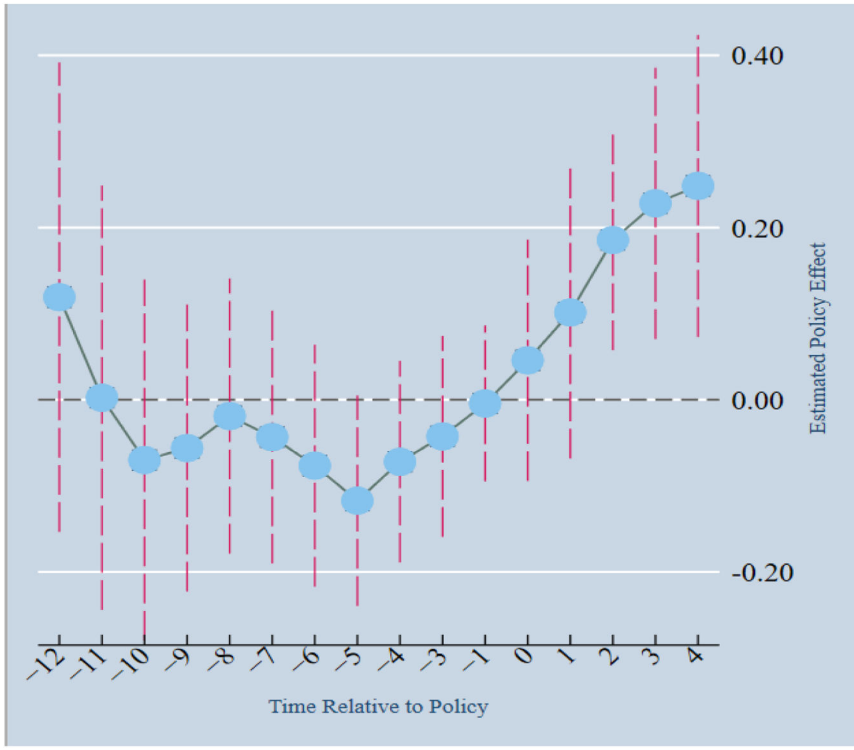

Fig. 3. Parallel trends test.

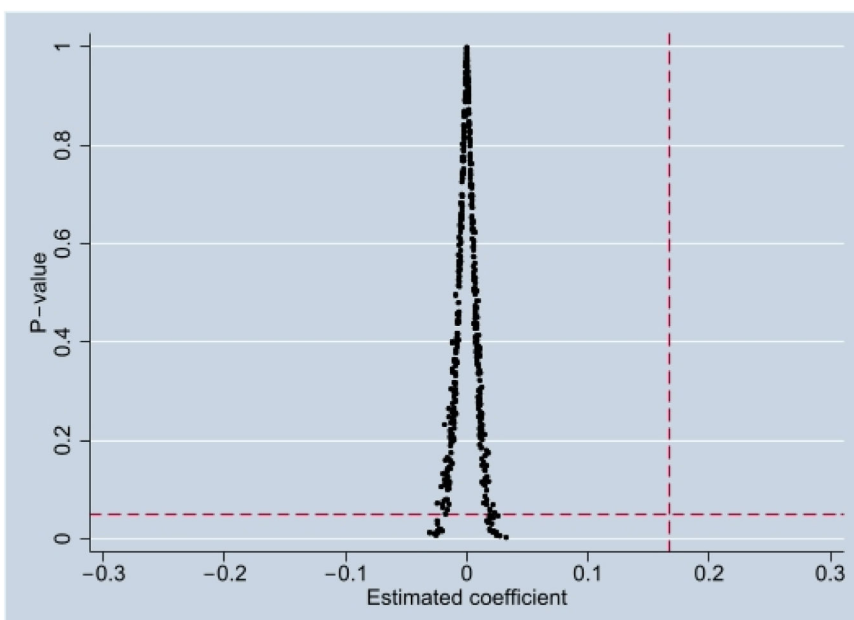

Fig. 4. Placebo test.

variables, the *DID* coefficient marginally decreases to 0.1678 and remains significant at the 1 % level. Including city-level controls does not substantially affect the core explanatory variable, indicating that regional economic development and industrial structure differences do not alter the policy's mechanism of action on corporate ESG performance.

Robustness checks

Parallel trends test

A fundamental requirement for applying the DID model is the parallel trends test, which aims to verify that treatment and control groups display consistent pre-policy trends in the dependent variable (Buckley & Shang, 2002). This test ensures the reliability of the policy effect estimation and excludes interference from other time-varying confounders. We employ an event study approach to construct a model, setting dummy variables for each year around policy implementation and interacting them with the treatment group dummy variable to capture dynamic effects before and after the policy. The model specification is as follows:

$$ESG_{i,t} = \alpha + \sum_{t=-n}^{-1} \beta_t (Treat_i \times Post_t) + \beta_0 (Treat_i \times Post_0) + \sum_{t=1}^{m} \beta_t (Treat_i \times Post_t) + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

Here, $Treat_i$ is a dummy variable for pilot zone firms (1 = in pilot zone, 0 = otherwise); $Post_t$ is a policy timing dummy variable, with $t = 0$ denoting the policy implementation year, $t = -n$ representing n years before implementation, and $t = m$ representing m years after implementation. The interaction term $Treat_i \times Post_t$ captures the effects of the treatment group each year. All the other variables are consistent with those in Model (1).

To avoid multicollinearity, $t = -2$ is selected as the reference period. As shown in Fig. 3, in the pre-policy period $t = -12$ to -1, the effect coefficients fluctuate around zero. They are insignificant, confirming that the treatment (pilot zone firms) and control (non-pilot zone firms) groups exhibited consistent ESG performance trends before the policy, satisfying the parallel trends assumption and supporting the applicability of the DID model. In years $t = 0$ to 1, the coefficients trend upward but are insignificant, likely because of the policy effects exhibiting a time lag. From the second to the fourth post-policy periods, $t = 2$ to 4, the coefficients are significantly positive and increasing, indicating that the pilot zone firms' ESG performance improved significantly relative to the non-pilot zone firms after policy implementation. This finding further validates the positive effect of the AI_IDPZ policy on corporate ESG performance, with the effect emerging and strengthening over time.

Placebo test

The placebo test is a critical step in empirical research to validate the robustness of conclusions; rule out the possibility that the estimation results are influenced by chance factors, unobserved variables, or model specification bias; and ensure that the identified policy effects are genuine and reliable (Eggers et al., 2024). This study examines robustness by fabricating the implementation objects and timing of the AI_IDPZ policy and re-estimating the model accordingly. As shown in Fig. 4, most of the estimated coefficients cluster around 0, with the corresponding p-values remaining high and showing no significant distribution pattern. This result indicates that no significant policy effects can be detected in the fictional policy scenarios. It also confirms that chance factors or model specification issues do not cause the results of the original study.

Table 3
PSM–DID and controlling for other policy interferences.

Variable	(1) *ESG*	(2) *ESG*	(3) *ESG*	(4) *ESG*
DID	0.1722***	0.1525***	0.1731***	0.1574***
	(0.0287)	(0.0314)	(0.0281)	(0.0308)
DID_Data		0.0484		0.0514
		(0.0362)		(0.0354)
DID_Broadband			−0.0402	−0.0437
			(0.0293)	(0.0288)
Constant	−0.4494	−0.2024	−0.1283	−0.1959
	(0.7256)	(0.6702)	(0.6682)	(0.6635)
Controls	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	36,829	36,829	36,829	36,829
R-squared	0.5231	0.5231	0.5231	0.5232

PSM–DID

The PSM–DID test addresses potential selection bias in the DID model (Zhai et al., 2022). Systematic differences in observable characteristics (control variables) between the treatment and control groups may confound the estimates because these characteristics influence both policy assignment and ESG outcomes. PSM mitigates selection bias by matching treatment and control firms based on observable covariates, ensuring pre-policy similarity before applying DID to estimate the causal effect.

The results in Column (1) of Table 3 align with the baseline regressions; even after rigorously controlling for selection bias, the positive effect remains statistically significant. This consistency validates the robustness of the baseline findings and demonstrates that the policy's impact on ESG performance is driven by the intervention itself and not by pre-existing observable differences between groups. These results strengthen the credibility of the conclusions and confirm the authenticity of the policy regardless of selection bias considerations.

Controlling for other policy interferences

To ensure the reliability of the research conclusions and exclude potential interference from other similar policies on corporate ESG performance, this study conducts robustness checks by incorporating two policies that are similar to the AI_IDPZ policy in promoting digital technology adoption and information infrastructure construction: the Broadband China (*DID_Broadband*) policy and the Big Data Comprehensive Pilot Zone (*DID_Data*) policy (Song et al., 2025). If these policies affect corporate ESG performance, they could confound the evaluation of the effects of the original policy. By integrating them into the analytical framework, we test whether the effect of the AI_IDPZ policy remains significant. As shown in Columns (2)–(4) of Table 3, the promoting effect remains statistically significant even after accounting for *DID_Broadband* and *DID_Data*. This result indicates that the research conclusions are not driven by interference from other similar policies, further validates the genuine and robust nature of the positive impact of the AI_IDPZ policy on corporate ESG performance, and strengthens the credibility and persuasiveness of the findings.

Mechanism analysis

Following existing research (Zhou et al., 2022), this study uses a mediation effect model to analyze the transmission channels, specifying the following models. Model (1) estimates the total effect.

$$M_{i,t} = \alpha + \theta DID_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

In Model (3), $M_{i,t}$ represents the mediator variable, with the same control variables, fixed effects, and error term as in the baseline model. A significant coefficient θ suggests the policy effectively drives changes in the mediator.

$$ESG_{i,t} = \alpha + \theta_1 DID_{i,t} + \theta_2 M_{i,t} + \gamma X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

In Model (4), controlling for the policy variable and other variables consistent with the baseline model. θ_1 represents the direct effect of the policy on ESG performance after controlling for the mediator $M_{i,t}$ while θ_2 reflects the mediator's impact on ESG, i.e., the transmission path. If

Table 4
Mediation mechanism test results.

Variable	(1) *DIGI_text*	(2) *ESG*	(3) *Green_innov*	(4) *ESG*	(5) *CSR*	(6) *ESG*
DID	0.0027***	0.1648***	0.0074***	0.1672***	0.1372**	0.1644***
	(0.0008)	(0.0284)	(0.0025)	(0.0288)	(0.0691)	(0.0288)
DIGI_text		1.0994***				
		(0.3905)				
Green_innov				0.0900**		
				(0.0453)		
CSR						0.0249***
						(0.0035)
Constant	−0.0934***	−0.0352	0.0708	−0.1443	−2.1577	−0.0842
	(0.0190)	(0.6756)	(0.0732)	(0.6736)	(2.6212)	(0.6743)
Controls	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	36,829	36,829	36,829	36,829	36,829	36,829
R-squared	0.8074	0.5232	0.4691	0.5231	0.6550	0.5246

Table 5
Catching-up effect of digital technological innovation.

	Regional Digital Economic Development		Corporate Digital Transformation	
	(1) Low	(2) High	(3) Low	(4) High
Variable	*ESG*	*ESG*	*ESG*	*ESG*
DID	0.2119***	0.0353	0.1670***	0.1359**
	(0.0398)	(0.0656)	(0.0316)	(0.0540)
Constant	0.1309	−6.2427	0.1673	−1.5974
	(0.8477)	(5.9448)	(0.7548)	(2.0365)
Controls	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	26,075	10,530	27,083	9160
R-squared	0.5530	0.6200	0.5378	0.5878

both θ_1 and θ_2 are significant, a partial mediation effect exists; if θ_2 is significant but θ_1 is not, a complete mediation effect is indicated. As shown in Table 4, the mechanism test results are all significant at the 1 % and 5 % levels.

Digital transformation

Column (1) of Table 4 shows that the *DID* coefficient on *DIGI_text* is 0.0027, indicating that the AI_IDPZ policy significantly promotes corporate digital transformation. Column (2) of Table 4 includes both *DID* and the digital transformation variable: the *DIGI_text* coefficient on *ESG* is 1.0994, and the *DID* coefficient remains 0.1648, showing no substantial attenuation relative to the total effect while maintaining significance. This result confirms that digital transformation acts as a partial mediator: the policy indirectly enhances ESG performance by promoting digital transformation and exerts a direct effect, thus validating the mediation mechanism.

Green innovation

Column (3) of Table 4 shows the *Green_innov* coefficient on *Green_innov* is 0.0074, indicating that the policy effectively drives corporate green innovation activities. Including the green innovation variable in Column (4) of Table 4, the coefficient of *Green_innov* on *ESG* is 0.0900 while the *DID* coefficient remains 0.1672. This result indicates that the policy indirectly enhances ESG performance by incentivizing green innovation, directly improving environmental performance and the societal recognition of corporate sustainability, with the policy's direct effect on ESG still present. The mediation mechanism is validated.

CSR information disclosure

Column (5) of Table 4 shows that the *DID* coefficient on *CSR* is 0.1372, indicating that the policy encourages firms to disclose more CSR information. Including the CSR variable in Column (6) of Table 4, the *CSR* coefficient on *ESG* is 0.0249 while the *DID* coefficient remains 0.1644, which is stable relative to the total effect. This result confirms that CSR acts as a partial mediator: the policy improves ESG performance indirectly by enhancing information disclosure, reducing stakeholder information asymmetry, and strengthening social legitimacy and governance transparency. Thus, Hypothesis 1 is validated.

Table 6
Technological innovation and market participation: Drivers of the catching-up effect in digital technological innovation.

	Heterogeneity in Technological Innovation Types		Heterogeneity in Ownership Structure	
	(1) High-tech	(2) Non-high-tech	(3) SOEs	(4) Non-SOEs
Variable	*ESG*	*ESG*	*ESG*	*ESG*
DID	0.1903***	0.1435***	0.1102*	0.1893***
	(0.0368)	(0.0444)	(0.0573)	(0.0301)
Constant	−0.1350	−0.3028	−1.6109	−0.4091
	(0.8728)	(1.0141)	(1.1750)	(0.8933)
Controls	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	21,234	15,307	13,848	22,267
R-squared	0.5122	0.5402	0.5586	0.5326

Further analysis: the catching-up effect of digital technology and its drivers

Heterogeneity in digital economic development

Following Song et al. (2025), we categorize regions and firms into high/low groups based on regional digital economy development levels and firm-level digital transformation degrees.

In the low regional digital economy group (Column (1) of Table 5), the *DID* coefficient is 0.2119 and significant at the 1 % level, indicating that the policy has a more pronounced effect on ESG performance in regions with weak digital economic foundations.

In the high regional digital economy group (Column (2) of Table 5), the *DID* coefficient is only 0.0353 and is insignificant. This result aligns with technological catch-up theory: firms in late-developing regions, starting from lower digital technology bases, can more effectively break through technical bottlenecks via policy-driven AI adoption, achieving "leapfrog" improvements in environmental management, CSR, and governance and thereby narrowing ESG gaps with leading regions. By contrast, firms in high digital economy regions may already have mature digital technology systems, leading to diminishing marginal policy effects.

As shown in Columns (3)–(4) of Table 5, in the low firm level digital transformation group, the *DID* coefficient is 0.1670 (significant at the 1 % level); in the high digital transformation group, it decreases to 0.1359 (significant at the 5 % level), with a notably smaller absolute value. This result shows that firms with weaker digital transformation foundations benefit more from policy-supported digital technology innovations in improving ESG performance, reflecting the latecomer advantage of "catching-up" firms through external policy empowerment. High digital transformation firms with accumulated technical capabilities experience limited incremental policy effects, further confirming the dominant role of the catching-up effect in the relationship between digital technological innovation and corporate ESG improvement.

Based on these heterogeneity analyses of regional digital economy development and firm-level digital transformation, the promoting effect of the AI_IDPZ policy on corporate ESG performance reflects the significant catching-up effect of digital technological innovation. Thus, Hypothesis 2 is validated.

Heterogeneity in technological innovation types

To validate the sources of the catching-up effect of digital technological innovation, we divide the sample into high-tech and non-high-tech industries to explore technological innovation drivers and into SOEs and non-SOEs to examine market participation drivers. As shown in Columns (1) and (2) of Table 6, the *DID* coefficient for high-tech enterprises is 0.1903, which is significant at the 1 % level, reflecting the policy's reinforcing effect on technological leaders. For non-high-tech enterprises with weaker initial technological innovation capabilities, although the *DID* coefficient is 0.1435 (significant at the 1 % level), slightly lower than that for high-tech enterprises, policy-driven digital technology adoption overcomes the limitations of traditional business models, enabling "compensatory improvements" in environmental management, CSR practices, and other domains. Accordingly, these firms narrow their ESG gap with high-tech enterprises. These results indicate that the policy's empowerment of technological latecomers constitutes a critical technical driving path for the catching-up effect. Non-high-tech enterprises can achieve technological catch-up through external policy support by lowering the threshold for digital technology adoption, thereby enhancing their ESG performance.

Heterogeneity in ownership structure

The analysis of ownership heterogeneity reveals a market participation-driven catching-up mechanism through divergent policy effects on SOEs and non-SOEs.

The *DID* coefficient for SOEs is 0.1102, significant only at the 10 % level. This result may stem from their weaker market competition pressures and relatively insufficient innovation incentives. While enjoying resource advantages, their response speed and transformation efficiency for policy-driven digital technological innovation are slower.

By contrast, the *DID* coefficient for non-SOEs reaches 0.1893, which is significant at the 1 % level and is notably higher than that of SOEs. This result reflects more substantial innovative initiatives among non-SOEs with higher market participation: lacking "natural" resource endowments, they rely more on proactive AI technology adoption to boost market competitiveness. Market competition pressures drive these innovative behaviors, transforming policy-provided digital tools into active strategies for improving ESG performance and forming a transmission chain of "policy guidance–market competition–innovative catch-up." This impact highlights the critical role of market participation in driving the catching-up effect.

The catching-up effect of digital technological innovation embedded in the policy's ESG-promoting impact arises from the dual drivers of technological innovation and market participation. Their synergistic action promotes balanced improvements in corporate ESG performance. Thus, Hypothesis 3 is validated.

Conclusions, policy implications, and research limitations

This study leverages the AI_IDPZ policy as a quasi-natural experiment and employs a DID model using panel data on Chinese A-share listed firms from 2009 to 2023. It systematically investigates the impact of AI policy on corporate ESG performance and explores the "catching-up effect" driven by digital technological innovation. Our findings are statistically robust and have substantial theoretical and practical implications.

Key findings and theoretical comparison

Significance and robustness of policy effects

The baseline regression results show that the coefficient of the key explanatory variable, *DID*, remains significantly positive at the 1 % level even after controlling for firm- and city-level covariates, providing initial evidence that the AI policy significantly enhances corporate ESG performance. We conduct multiple validity checks to bolster the causal identification. First, the parallel trends assumption is validated through both graphical and interaction term-based analyses, confirming no significant pretreatment divergence in ESG trends between the treatment and control groups. Second, placebo tests based on pseudo-policy time points yield null effects, mitigating concerns about spurious results driven by time trends or external shocks. Third, we apply PSM–DID to address sample selection bias and improve comparability between the groups.

The robustness tests collectively affirm the causal inference and explanatory power of our findings. Furthermore, our results align with and extend those of previous research. Li et al. (2025) and Zhang and Yang (2024) find that AI adoption enhances environmental and social performance. Chen and Zhang (2025) emphasize the role of internal controls and information environment in transmitting AI's impact on ESG. Zhou et al. (2025) adopt a similar quasi-natural experiment and show that improved information governance underpins ESG gains from AI. Xiao and Xiao (2025) further confirm the sustainability-enhancing effects of AI-driven ESG practices on SOEs.

Relative to these studies, our work contributes to a more comprehensive empirical strategy through rigorous robustness tests and introduces an integrated theoretical framework based on twin transition and ESG theories. We also uncover the heterogeneous effects of AI policy across firm and regional characteristics, enriching the theoretical understanding and policy implications of the technology–sustainability nexus.

Mechanism analysis: dual pathways of technological and institutional response

Our mechanism analysis identifies three distinct channels through which AI policy enhances ESG performance: (1) it facilitates corporate digital transformation, thereby improving resource efficiency, smart decision-making, and environmental/governance outcomes; (2) it promotes green innovation, encouraging low-carbon technological investment and environmentally friendly production practices; and (3) it strengthens CSR information disclosure and enhances transparency and social responsiveness. These findings are consistent with the "technology integration-driven ESG upgrading" pathway proposed by Dzhengiz and Niesten (2020) and resonate with the central propositions in the twin transition literature emphasizing the synergy between digital and green innovation (Appio et al., 2021; Fouquet & Hippe, 2022; Rehman et al., 2023; Hofmann Trevisan et al., 2024).

Heterogeneity analysis: the catching-up effect of technological latecomers

Our heterogeneity analysis reveals a clear "catching-up effect": the AI policy has a stronger positive impact on ESG performance in firms with lower digital capabilities and in regions with underdeveloped digital economies. This finding supports the "latecomer advantage" and "leapfrogging" mechanisms in the technological catching-up theory (Lee & Lim, 2001). Moreover, the policy effect is more pronounced in high-tech and non-SOEs, highlighting the joint role of absorptive capacity and market incentives in driving ESG improvements, that is, the "capability + institution" dual-drive mechanism.

By contrast, most international research focuses on technology leaders in developed economies and tends to overlook the ESG upgrading pathways of technologically lagging firms. Our study provides novel empirical evidence from a transitional economy, that is, China, and demonstrates that latecomers can achieve ESG breakthroughs through digital transformation under proactive government guidance and effective technology diffusion.

Practical implications and policy recommendations

Our findings show that the AI_IDPZ policy significantly improves ESG performance, particularly for firms with weaker digital foundations. This result not only validates the institutional logic of technological empowerment for sustainability but also provides policy-relevant insights from China's experience in integrating green and digital transitions. Accordingly, we propose the following recommendations for different stakeholders.

For local governments: enhance precision and inclusiveness in policy implementation

As critical implementers of the AI_IDPZ policy, local governments should improve both inter-regional policy alignment and intra-regional policy accessibility. First, they should optimize fiscal incentives and resource allocation to prioritize firms with weak technological bases and high green transformation pressure, thereby promoting digital resource penetration into traditional sectors and small and medium-sized enterprises. Second, policy toolkits should be tailored to regional development stages and industrial structures, particularly in the central and western regions, to reduce digital inequality and ESG performance disparities. Third, fostering inter-regional policy coordination and experience sharing can enhance systemic synergy and scalability.

For central regulators and policymakers: build an integrated "Digital + ESG" governance system

Central authorities should promote the integration of digital technologies and sustainable governance at the institutional design level. On the one hand, accelerating the digital transformation of ESG disclosure systems and building AI- and big data-based green financial infrastructure will improve regulatory transparency and data accessibility. On the other hand, AI technologies should be incorporated into ESG rating systems, carbon disclosure mechanisms, and environmental risk monitoring tools to develop more scientific, transparent, and verifiable evaluation standards. A dynamic evaluation mechanism is also recommended to track and adjust policy effectiveness throughout the implementation process and thereby ensure that technological expansion and ESG goals advance simultaneously.

For corporate managers: embed ESG strategy in digital transformation pathways

Firms, as the ultimate executors of policy and carriers of ESG outcomes, should proactively embed ESG objectives into their digital strategies and develop governance capacities geared toward sustainability. First, managers should recognize the strategic synergy between AI and ESG and view ESG performance as integral to long-term value creation and risk mitigation. This undertaking includes systematically planning carbon reduction, resource efficiency, and governance transparency. Second, firms should invest in green R&D, smart management systems, and ESG disclosure platforms to build sustainable data-driven governance structures. Third, in line with regulatory trends and market expectations, companies should actively participate in ESG disclosure and rating initiatives; integrate social responsibility with incentive mechanisms to enhance resilience, transparency, and competitiveness; and transform from passive compliance to proactive leadership.

Limitations and future research directions

First, this study is based on a sample of A-share listed firms in China from 2009 to 2023. While listed companies offer reliable data owing to more standardized information disclosure, corporate governance, and policy responsiveness, this sample choice may limit the external applicability of our findings. Unlisted firms, especially small and medium-sized enterprises, often differ significantly in their digital infrastructure, technological absorptive capacity, and ESG implementation pathways (Ayinaddis, 2025). Whether our conclusions apply equally to these firms remains an open question for future research.

Second, China's institutional setting, policy execution style, and economic governance model are unique in many respects. For example, in the realm of digital policy implementation, the Chinese government exhibits strong organizational capacity and centralized resource allocation mechanisms, which may amplify the effectiveness of policies in improving ESG performance. By contrast, in countries with more decentralized institutions and market-oriented governance, the relationship between AI policy and corporate sustainability may manifest differently. Future research could incorporate a cross-country comparative perspective to explore how institutional and governance differences shape policy impacts.

Finally, while this study focuses on the static effects and heterogeneity mechanisms of AI policy on ESG performance, future research could explore the dynamic evolution of policy impacts. This undertaking includes investigating how the diffusion of AI technologies within firms gradually translates into long-term ESG capacity-building. Additionally, as ESG rating standards become increasingly diversified and data transparency improves, future studies could use multisource ESG data for cross-validation, thereby enhancing the robustness and explanatory power of the results.

CRediT authorship contribution statement

Yinghao Song: Funding acquisition, Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Long Mi:** Validation. **Zhaian Bian:** Validation, Supervision, Methodology. **Wei Tu:** Validation, Supervision. **Juan He:** Validation, Project administration, Formal analysis.

Declaration of competing interest

The authors declare no competing interests.

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