

Does Enterprise Digitalization Promote the Green and Low-carbon Transformation and Upgrading? Evidence from A-share Listed Companies in China

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As the world's top emitter of greenhouse gases, China's acceleration of emission mitigation is critical for global climate governance. Enterprises, as core economic actors, play a pivotal role in achieving sustainable development through green and low-carbon transformation (GLCT), a cornerstone of China's carbon peaking and neutrality objectives. This study examines whether enterprise digitalization—a key driver of digital-real economy integration—facilitates reductions in corporate greenhouse gas and pollutant emissions, thereby advancing GLCT. Utilizing 2008–2020 data from Chinese listed firms, we investigate the mechanisms underlying this relationship and heterogeneity across enterprises. Results reveal that digitalization significantly lowers emission intensity via pathways such as technological innovation, efficiency gains, operational environment optimization, and structural adjustments. Heterogeneity analysis highlights stronger effects in state-owned enterprises and competitive industries, with no regional regulatory disparities observed. This study demonstrates that digitalization significantly contributes to corporate green and low-carbon transition (GLCT) by reducing carbon and pollutant emission intensities. Empirical evidence reveals four critical mechanisms driving this transformation: technological innovation enhancement, operational efficiency optimization, managerial environment improvement, and production structure reorganization. Heterogeneity analysis highlights pronounced GLCT effects in state-owned enterprises and firms within hypercompetitive industries, while environmental regulation intensity shows negligible regional differentiation. The research systematically examines enterprise pathways for emission reduction in digital contexts, establishing a theoretical framework for achieving carbon neutrality goals. The findings inform policymakers in developing tailored digital strategies aligned with enterprise capabilities and sectoral attributes.

Keywords: Digitalization; Carbon Emission Intensity; Pollutant Emission; Green and Low-Carbon Transformation.

Introduction

Global climate change necessitates coordinated international mitigation efforts. For economies undergoing industrialization, reconciling resource conservation with energy-intensive growth models presents a significant developmental paradox. This challenge manifests acutely in greenhouse gas mitigation strategies, prompting governmental prioritization of carbon abatement while sustaining economic momentum. Corporate green transition emerges as a pivotal mechanism for achieving sustainable development goals. National policy frameworks increasingly emphasize low-carbon transformation, with carbon peaking and neutrality objectives elevated to strategic priorities, reflecting institutional commitments to harmonize ecological preservation with economic advancement. This paradigm underscores the imperative for innovative approaches to industrial decarbonization within evolving environmental governance systems.

China's pursuit of carbon neutrality necessitates coordinated efforts toward green, low-carbon development pathways. Enterprise adoption of environmentally sustainable production methods constitutes a strategic priority for achieving ecological governance and quality economic growth.

Digital innovation presents transformative opportunities for organizational transitions to cleaner operations. Emerging evidence suggests that digital technology deployment may enhance operational efficiency and resource optimization within enterprises (Lu & Li, 2024; Fu *et al.*, 2024), potentially enabling better process supervision and subsequent emission mitigation (Gao *et al.*, 2023; He & Chen, 2023). However, contrasting perspectives highlight potential counteractive effects, with arguments that digital adoption might paradoxically stimulate increased energy demand through efficiency-driven consumption rebounds (Zhou *et al.*, 2018; Liao *et al.*, 2023) or escalate carbon outputs under certain conditions (Lange *et al.*, 2020). These contradictory outcomes underscore the imperative to systematically investigate the operational mechanisms through which digital transformation interacts with corporate environmental performance. Scholarly inquiry must prioritize elucidation of how digital solutions can be strategically aligned with sustainability objectives, particularly regarding their capacity to reconcile environmental targets with economic imperatives. Such examination would advance theoretical frameworks for understanding the complex dynamics between technological modernization and ecological stewardship in industrial contexts.

This empirical analysis explores the linkage between enterprise digitalization and green-low carbon transition (GLCT) using Chinese A-share listed firms' data. Departing from macro-level emission studies, it employs firm-level metrics to assess digital transformation's role in emission mitigation, advancing microeconomic perspectives on sustainable industrial transitions (Zhou *et al.*, 2018). The research innovatively identifies transmission mechanisms by which digitalization facilitates GLCT, including technology innovation, production efficiency enhancement, operational environment optimization, and structural adjustments in production processes (Hilty & Aebische, 2015; Murshed, 2020; Li *et al.*, 2021). Furthermore, it conducts heterogeneity analyses across enterprise characteristics, advancing beyond conventional studies on digitalization-emission linkages to offer differentiated insights (Wang *et al.*, 2023). By establishing theoretical frameworks and empirical evidence, this work provides policymakers with valuable references for developing targeted strategies that accommodate enterprise-specific conditions, thereby supporting sector-wide implementation of green transformation objectives. The results guide business actions in line with carbon neutrality objectives and advance scholarly knowledge of the applications of the digital economy in sustainable development. (Liu *et al.*, 2022; Xu *et al.*, 2022b).

Section II reviews theoretical frameworks, III outlines methodology, IV presents empirical findings, V-VI examine digitalization pathways for GLCT advancement, and VII concludes with policy insights. The study systematically explores corporate digital transformation's role in sustainable transition mechanisms.

Literature Review and Theoretical Analysis

Literature Review

Existing scholarship explores digital-green technology convergence and examines connections between organizational digital transformation and sustainable enterprise operations.

Digital Economy and Green Sustainable Development

This study examines the critical role of digitalization in advancing green technology innovation and carbon mitigation. Empirical evidence demonstrates that digital transformation facilitates breakthroughs in clean energy technologies, thereby improving CO₂ treatment efficiency and reducing emission intensity. Following established methodologies (Chapple *et al.*, 2013; Lin & Jia, 2019), this analysis employs green patent counts (lnGPat) as proxies for eco-innovation, supplemented by R&D expenditure ratios (RD) and patent typology analyses distinguishing utility (lnipat) vs. design patents (lnides), as well as collaborative (lnunit) vs. independent innovations (lnind). The results confirm Hypothesis 2 through statistically significant positive coefficients for digitalization variables, substantiating its capacity to enhance corporate innovation ecosystems. These results are consistent with earlier studies (Xu *et al.*, 2022b), highlighting technological innovation as a crucial means of accomplishing carbon neutrality goals (Dai *et al.*, 2022).

Micro-level analyses demonstrate ambivalent effects of digital transformation on corporate environmental outcomes.

While technological modernization facilitates green innovation through enhanced R&D capabilities (Wen *et al.*, 2022; Ma & Tao, 2023) and improves operational resource allocation (Cao *et al.*, 2023), contrary observations highlight energy intensification risks in traditional ICT frameworks (Zhou *et al.*, 2018; Lv *et al.*, 2022). The efficiency paradox manifests when technological optimization inadvertently stimulates consumption expansion (Wang *et al.*, 2019; Ke *et al.*, 2022), creating rebound effects that offset sustainability gains. Recent scholarship (Meng & Zhao, 2022; Li, 2022) reveals complex nonlinear patterns in digital-environmental interactions, emphasizing threshold effects where ecological benefits materialize only beyond specific technological adoption levels. This duality necessitates balanced strategies that harness digital advantages while mitigating energy consumption externalities.

Digital Technology and Green Sustainable Development

Emerging research underscores enterprises as critical agents in sustainable transitions, with digitalization emerging as a strategic enabler of low-carbon development. Empirical studies demonstrate that technological advancement (Huang *et al.*, 2020) and regulatory interventions (Li *et al.*, 2021) synergistically drive emission reductions, augmented by market-driven mechanisms like carbon trading (Yang *et al.*, 2023). Digital capabilities facilitate resource optimization and eco-innovation through enhanced data utilization (Ning *et al.*, 2022), creating systemic operational efficiencies that cascade into environmental benefits (Liu & Chen, 2022). This synergy between digital infrastructure and green innovation pathways positions organizational digitization as a multidimensional solution for achieving climate commitments.

Geospatial factors enter the analytical framework through debates on emission patterns. While empirical evidence reveals divergent patterns where industrial cluster configurations may alter pollution trajectories (Wang *et al.*, 2023), counter analyses emphasize industrial parks' persistent emission dominance (Yan *et al.*, 2022). The environmental duality of digital adoption surfaces through infrastructure paradoxes - energy-intensive digital operations (Li *et al.*, 2020) potentially neutralizing eco-efficiency improvements. Theoretical frameworks propose complex nonlinear interactions, featuring emission thresholds (Li *et al.*, 2021) and inverted U-curve correlations between digital maturity and environmental impact (Li & Wang, 2022). These complexities necessitate cautious interpretation of digitalization's role, as improper implementation pathways might paradoxically impede sustainability transitions (Usai *et al.*, 2021). Persistent academic divergences highlight fundamental uncertainties in modeling digital-environmental interfaces.

Mechanism Analysis

Innovation-driven Effect

The integration of digital technologies into enterprise operations has been demonstrated to strengthen technical innovation capabilities, primarily through enhanced data analytics and automated systems (Hilty & Aebische, 2015; Zhao *et al.*, 2023). This technological progression enables enterprises to refine operational efficiency, optimize

resource allocation, and reduce production expenditures (Keskin *et al.*, 2023). By leveraging digital tools, organizations can systematically identify and address inefficiencies within production workflows, thereby establishing more sustainable energy consumption patterns (Rizzoli *et al.*, 2015; May *et al.*, 2017). Such digital-driven operational transformations are posited to create pathways for reducing carbon emissions through improved process management and energy stewardship (Xu *et al.*, 2022a). According to the above analysis, hypothesis 1 is proposed as follow:

Hypothesis 1: Enterprise digitalization can improve technology innovation and further promote green and low-carbon transformation of enterprises.

Efficiency Promotion Effect

The integration of digital technologies within enterprises demonstrates multifaceted potential for improving environmental sustainability. Scholarly investigations highlight two primary mechanisms through which digitalization enhances operational efficiency. First, it facilitates cross-departmental knowledge dissemination and mitigates organizational information asymmetries, thereby refining the accuracy of resource distribution (Ma *et al.*, 2023; Li & Zhao, 2024). Second, digital infrastructure empowers firms to systematically identify suboptimal energy management practices across production and distribution networks (Hao *et al.*, 2022). Advanced analytical tools enable real-time monitoring and process optimization, streamlining energy utilization while minimizing systemic waste (Wang *et al.*, 2021; Bashynska *et al.*, 2023). Such operational enhancements create cascading effects on ecological outcomes, particularly through reduced emission intensities (Murshed, 2020). These interconnected pathways form the theoretical foundation for subsequent hypothesis development regarding digitalization's environmental impacts. On the basis of the above analysis, hypothesis 2 was proposed as follow:

Hypothesis 2: Digitalization can improve the production efficiency of enterprises, thereby facilitating their green and low-carbon transformation.

Improvement of Operating Environment

The integration of digital technologies within enterprises addresses information asymmetry through multiple pathways. By facilitating cross-functional collaboration and amplifying knowledge spillovers in low-carbon innovation (Meng *et al.*, 2023; Jing *et al.*, 2023), digitalization enables synergistic advancements in sustainable practices. Enhanced regional industrial connectivity through digital platforms further reduces informational gaps and curtails redundant infrastructure development (Berliant *et al.*, 2014; Zhang, 2023). Financially, digitized information systems lower capital acquisition barriers, easing fiscal constraints that hinder eco-friendly initiatives (Yu *et al.*, 2021; Wang *et al.*, 2022a). Operationally, data-driven sales strategies improve production-marketing coordination through real-time consumer insights (Okorie *et al.*, 2024), enabling customized output while mitigating market saturation risks (Zhao & Ren, 2023). Concurrently, predictive analytics in supply chain management minimizes resource overutilization and associated environmental impacts (Tang, 2023). These mechanisms collectively substantiate the theoretical

proposition regarding digitalization's role in organizational and ecological optimization. In view of the above analysis, hypothesis 3 is hereby raised:

Hypothesis 3: Digitalization can promote the green and low-carbon transformation of enterprises by improving their external operating environment.

Optimization of Production and Operating Structure

Enterprise digital transformation extends across organizational ecosystems, integrating manufacturing systems with supply chain networks (May *et al.*, 2017; Majdalawieh and Khan, 2022). Operational integration of digital tools enables dynamic reconfiguration of production factors (Ji *et al.*, 2023), fostering structural optimization of workflows and enhancing allocative efficiency (Zhang & Zhang, 2023). Workforce development emerges as a critical dimension, with digital adoption facilitating talent acquisition and competency-based organizational restructuring (Acemoglu & Restrepo, 2018; Li *et al.*, 2023). Process innovation through digital integration supports lean manufacturing paradigms (Higon *et al.*, 2017; Ren *et al.*, 2023), enabling precision resource management that reduces environmental footprints (Peng *et al.*, 2023). Structural evolution within production systems promotes functional specialization and adaptive operational models (Steen *et al.*, 2019; Xu *et al.*, 2023), creating systemic pathways for emission mitigation (Gao *et al.*, 2023). These multidimensional interactions form the theoretical basis for subsequent investigative propositions. Because of the above analysis, hypothesis 4 was proposed as follow:

Hypothesis 4: Digitalization can promote the green and low-carbon transformation of enterprises by optimizing enterprises internal operating structure.

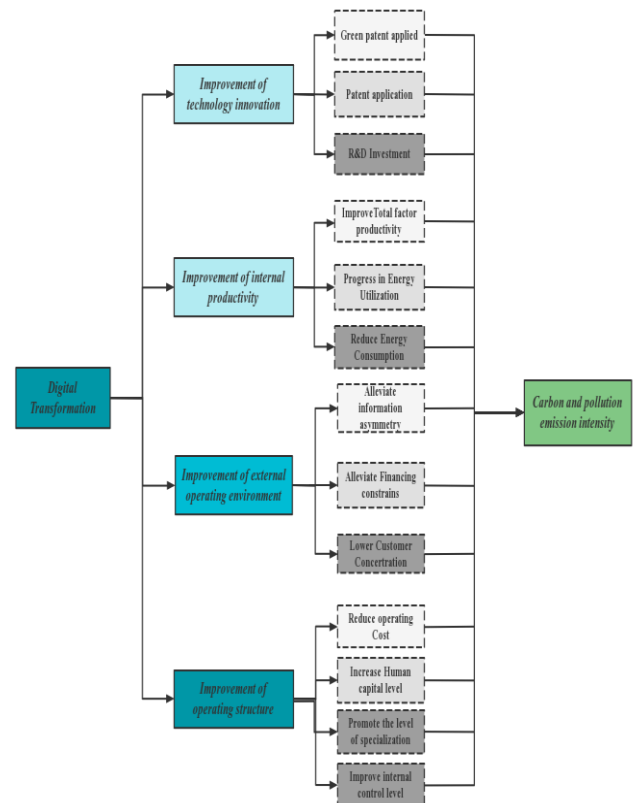


Figure 1. The Key Pathways Enterprise Digitalization Influences the Intensity of Carbon and Pollution Emission

Research Design

Description of Variables

1. Explained variables: CO₂ emission intensity (*intenco2*) and pollutant emissions of enterprises. Due to the lack of mandatory carbon disclosure frameworks, corporate CO₂ emissions were indirectly estimated using sectoral energy consumption profiles and methodological adaptations from Chapple et al. (2013). Emission intensity metrics were constructed through logarithmic ratios of emissions to operational income, supplemented by robustness checks utilizing non-logarithmic emissions per unit income and production output. The estimation framework leveraged industry-specific energy utilization patterns to infer firm-level emissions. The calculation formula used in this study is as follows:

$$em_{it} = \frac{cos_f_{it}}{cost_i_{jt}} \times TEC_{jt} \times 2.493 \quad (3-1)$$

$$intenco2_{it} = \ln\left(\frac{em_{it}}{income_f_{it}} \times \frac{1}{1000000}\right) \quad (3-2)$$

In the given formula, *i* represents enterprises while *j* represents industries. *em_{it}* denotes the CO₂ emissions of enterprises, *income_{f_{it}}* refers to the main operating income of enterprises, and *intenco2_{it}* denotes the carbon emission intensity of company. *cos_{f_{it}}* and *cost_{i_{jt}}* refer to the main operating costs of enterprises and the industry respectively. Corporate data was sourced from CSMAR, with coal-related CO₂ emissions calculated using standardized conversion coefficients from regional energy guidelines (Lin & Jia, 2019).

This study operationalizes enterprise pollutant outputs through industrial airborne contaminants (SO₂, NO_x) and wastewater indicators (COD, NH), measured via logarithmic pollution equivalence values derived from regulatory emission assessment frameworks. The metric aligns with administrative protocols for emission fee collection, providing a standardized comparative basis for quantifying contaminant discharges. Logarithmic transformation of pollution equivalence values enhances cross-scale comparability while mitigating distributional skewness inherent in raw emission data, thereby improving analytical precision in environmental performance evaluation.

2. Core explanatory variable: Level of enterprise digitalization (*digital*). The measurement of this variable involves text analysis. A vocabulary library was established, comprising indicators associated with cloud computing, big data, digital technology, blockchain technology, and artificial intelligence (AI) technology, derived from enterprise annual reports.

This study employs computational textual analysis to assess enterprise digitalization levels through annual report disclosures. Digital transformation intensity was quantified by logarithmic transformation of adjusted lexical frequencies, where higher index values correlate with increased technological adoption. Such methodology operationalizes textual indicators as proxies for organizational digital maturity.

3. Control variables. This paper incorporates additional control variables influencing the reduction of carbon

emission in enterprises, including company age (*age*), asset-liability ratio (*lev*), return on equity (*roe*), operating cash flow (*cf*), sales growth rate (*growth*), net profit growth rate (*gprofit*), ratio of tangible assets (*Tangibi*), board size (*board*), ratio of independent directors (*indep*), shareholding ratio of the top shareholder (*Top1*), and nature of property rights (*soe*, with a value is 0 for state-owned companies and 1 for private companies).

Model Design

To prove the influence of digitalization of Chinese companies on their emission reduction, the following models were designed in this paper:

$$intenco2_{it} = \alpha_0 + \alpha_1 Digit_{it} + \sum \alpha_k Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3-3)$$

$$Pollution_{it} = \beta_0 + \beta_1 Digit_{it} + \sum \beta_k Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3-4)$$

Where, *intenco2_{it}* represents the carbon emission intensity of enterprise *i* in the *tth* year. *Pollution_{it}* refers to the emission of pollutants at the enterprise level. The core explanatory variable is *Digital_{it}*, which refer to the digitalization level of enterprise *i* in the *tth* year. While *μ_i* and *λ_t* represent the firm and year fixed effect respectively. *ε* denotes residual.

Data Source

This analysis utilizes panel data from Chinese A-share listed enterprises, with financial institutions, specially treated entities, and incomplete records systematically excluded. Primary operational metrics were sourced from CSMAR, supplemented by textual disclosures extracted from WIND's annual report repository. To mitigate extreme value distortions, continuous non-ratio variables underwent winsorization prior to analytical processing. The methodological framework ensures data integrity while maintaining alignment with conventional corporate governance research protocols.¹

Analysis of Empirical Results

Analysis of Benchmark Results

The regression analysis in the study evaluates models (3-3) and (3-4) by incorporating firm-specific control variables alongside fixed effects for year, firm, industry, and city. As shown in Table 1, enterprise digitalization exhibits statistically significant negative coefficients across air and water pollutant emissions, aligning with methodologies outlined by Chapple et al. (2013). These findings suggest that digital adoption is inversely correlated with emission intensity, reinforcing its potential role in advancing green transition. The robustness of the results is underscored by consistent patterns in waste gas and wastewater pollutant indicators, supporting the broader inference that digital integration aligns with sustainable practices (Zhou et al., 2018; Li & Wang, 2022). The analytical framework emphasizes enterprise-level dynamics, bridging gaps in prior macro-focused research while retaining theoretical linkages to innovation and efficiency pathways (May et al., 2017; Xu et al., 2022a)

¹ Please refer to Appendix Table 1 for statistical description of related variables.

Table 1

Benchmark Regression					
	<i>co2 emission</i>	<i>Air pollution emission</i>		<i>Water pollution emission</i>	
	lnintenco2	SO2	NOX	COD	NH
	(1)	(2)	(3)	(4)	(5)
<i>digital</i>	-0.3498*** (0.1157)	-0.0425*** (0.0138)	-0.0473*** (0.0060)	-1.1254*** (0.2114)	-0.0292*** (0.0037)
<i>Top1</i>	-6.7780** (3.3678)	-0.8173* (0.4380)	-0.2297* (0.1378)	-4.5299 (3.8174)	-0.1802** (0.0809)
<i>Indep</i>	5.3040* (3.0814)	0.7132* (0.3998)	-0.1401 (0.1446)	3.6798 (4.4756)	-0.0781 (0.0887)
<i>Board</i>	-0.3703 (0.9146)	-0.0322 (0.1178)	-0.2543*** (0.0922)	-4.9073* (2.6792)	-0.1451*** (0.0545)
<i>Age</i>	-1.0958*** (0.2898)	-0.1058*** (0.0375)	-0.2470*** (0.0274)	-6.9732*** (0.9501)	-0.1447*** (0.0164)
<i>Roe</i>	2.3649* (1.3122)	0.2167 (0.1651)	-0.0595 (0.0738)	-0.3903 (2.7384)	-0.0180 (0.0454)
<i>Tangibility</i>	1.2620 (1.4768)	0.1530 (0.1749)	0.1911 (0.1236)	3.2536 (3.6191)	0.0967 (0.0768)
<i>Growth</i>	0.7289*** (0.2278)	0.0618** (0.0281)	-0.1251*** (0.0154)	-3.1150*** (0.6076)	-0.0739*** (0.0092)
<i>cf</i>	4.3634*** (1.1514)	0.4669*** (0.1479)	0.0587 (0.0704)	-2.0957 (2.7420)	0.0199 (0.0436)
<i>Lev</i>	1.3225 (1.5238)	0.0928 (0.2025)	-0.4782*** (0.0955)	-9.4832*** (2.9331)	-0.2887*** (0.0586)
<i>Gprofit</i>	-2.4767 (1.8456)	-0.2843 (0.2038)	-0.3844*** (0.1135)	-9.9796*** (3.6610)	-0.2698*** (0.0683)
<i>Industry FE</i>	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes
<i>N</i>	18,468	18,468	16,543	16,543	16,543
<i>R²</i>	0.214	0.201	0.812	0.581	0.802

Robustness Test

Endogenous Treatment

To address potential endogeneity concerns, this study adopts complementary methodologies grounded in established econometric approaches. First, leveraging the Bartik instrumental variables framework (Autor *et al.*, 2013), an instrumental variable is constructed by interacting lagged industry-level digitalization indicators with nationwide internet user growth rates, excluding regional overlaps to satisfy exogeneity requirements. This design aligns with theoretical assumptions that the IV correlates strongly with enterprise digitalization while remaining orthogonal to unobserved confounders. Second, system GMM and difference GMM estimators (Blundell & Bond,

1998; Arellano & Bover, 1995) are implemented to account for dynamic panel biases and unobserved heterogeneity. These methodologies mitigate simultaneity and omitted variable concerns through lagged instruments and first-differenced equations, enhancing causal inference robustness. By synthesizing cross-sectional IV strategies with longitudinal panel techniques, the analysis systematically addresses identification challenges inherent in assessing digitalization's environmental impacts (Havranek *et al.*, 2015). The methodological synergy strengthens empirical validity while adhering to conventional practices in energy economics literature (Wang *et al.*, 2016; Cheng & Jin, 2023). The regression results can be seen from Table 2.

Table 2

Endogenous Regression ²				
Panel A	Instruments Regression		System GMM	Diff-GMM
<i>co2 emission</i>	digital	lnintenco2	lnintenco2	lnintenco2
	First stage	Second stage		
	(1)	(2)		
<i>IV</i>	18.6262*** (3.4470)			
<i>digital</i>		-0.5737**	-0.6916**	-0.8049***

² Due to limited space, only system GMM and differential GMM regressions of carbon emission intensity is given here, and the GMM regression of air and water pollutant emissions is also robust.

Panel A	Instruments Regression		System GMM	Diff-GMM
		(-0.2109)	(0.2767)	(0.1978)
Panel B	Air pollution		Water pollution	
Pollution Emission	SO2	NOX	COD	NH
	Second stage	Second stage	Second stage	Second stage
	(5)	(6)	(7)	(8)
<i>digital</i>	-0.6141** (0.3029)	-0.6685** (0.2960)	-16.9129** (8.6771)	-0.3969** (0.1695)
<i>Control variable</i>	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes
<i>Industry FE</i>	no	yes	yes	yes
<i>City FE</i>	no	no	yes	yes
<i>LM Statistics</i>	12.217***			
<i>F</i>	38.670***			

The instrumental variable analysis in Panel A demonstrates a statistically significant association between the Bartik IV and corporate digitalization, with diagnostic tests confirming the instrument's validity through rejection of underidentification and weak instrument hypotheses at conventional significance levels. Subsequent columns present regression outcomes where the digitalization coefficient retains its negative directionality, reinforcing the robustness of the core findings. To address endogeneity concerns arising from model specification and omitted variables, supplementary estimations employing system GMM and difference GMM methodologies are implemented. These alternative approaches yield consistent directional patterns, corroborating the initial results from the instrumental variable framework. The convergence of evidence across multiple econometric techniques – including IV regressions and dynamic panel models – substantiates the inverse relationship between enterprise digitalization and carbon emissions, thereby strengthening the analytical credibility of the study's central proposition (Zhou *et al.*, 2018; Wang *et al.*, 2019; Lyu *et al.*, 2023). The analysis of gaseous and aqueous pollutant emissions in Panel B demonstrates methodological consistency through instrumental variable approaches. Empirical estimates across multiple specifications reveal statistically significant inverse associations between digitalization levels and emission intensities (Zhou *et al.*, 2018; Lv *et al.*, 2022). These findings align with prior analyses, reinforcing the robustness of the proposed relationship between technological adoption and environmental performance metrics. The persistent negative correlation across diverse pollutant categories substantiates the premise that digital transformation contributes to emission mitigation strategies (Wang *et al.*, 2019; Ke *et al.*, 2022). Such empirical patterns corroborate theoretical frameworks positing digitalization as a catalyst for sustainable operational practices (Meng & Zhao, 2022; Li, 2022). The convergence of results across analytical models and emission types enhances confidence in the study's conceptual framework while underscoring the multidimensional nature of digital-environmental interactions (Dou & Gao, 2022; Nham, 2022). This evidentiary consistency strengthens the foundation for examining technological pathways in ecological modernization.

Difference-in-Difference (DID)

The enterprises which promote digitalization in stages provide an appropriate quasi-natural experiment for this research. Hence, the current research used the difference-in-difference (DID) model differentiate between two groups of listed companies engaged in digital events, so as to minimize internal disparities among relevant individuals and the estimation error resultant from time trends irrelevant to the experimental group, in order to achieve precise results about the influence of digitalization on enterprise's carbon reduction. This paper established formulas (4-1)–(4-3) to validate that impact.

$$intenco2_{it} = \alpha + \alpha_1 du_{it} + \alpha_2 dt_{it} + \alpha_3 (du_{it} \times dt_{it}) + \sum \varphi CVs + \varepsilon \quad (4-1)$$

$$intenco2_{it} = \beta_0 + \beta_1 (du_{it} \times dt_{it}) + \sum year + \sum firm + \sum \varphi^* CVs + \varepsilon \quad (4-2)$$

$$intenco2_{it} = \gamma_0 + \beta_1 (du_{it} \times dt_{it} \times digital) + \sum year + \sum firm + \sum \varphi^{**} CVs + \varepsilon \quad (4-3)$$

The analytical framework incorporates dichotomous indicators to capture digital transition dynamics: du_{it} denotes enterprise adoption status, while dt_{it} tracks temporal implementation patterns. The interaction term $du_{it} \times dt_{it}$ isolates temporal emission variations following digital adoption. Model specifications progressively introduce fixed effects for organizational and temporal heterogeneity, with subsequent extensions integrating digitalization intensity metrics (Higon *et al.*, 2017; Ren *et al.*, 2023). The multiplicative term $du_{it} \times dt_{it} \times digital$ quantifies how implementation depth modulates emission trajectories, operationalizing digital maturity as a continuous moderating factor (Acemoglu & Restrepo, 2018; Li *et al.*, 2023). This staged modeling approach disentangles temporal, categorical, and intensity-based dimensions of technological transitions in environmental performance analysis.

The DID approach was applied to estimate the causal relationship between digitalization and emission reduction effects. Column (1) in Table 3 reports the regression results of Eq. (4-1), where the significantly negative coefficient of $du_{it} \times dt_{it}$ implies a notable decline in corporate carbon emission intensity post-digital transformation. To enhance methodological rigor, Eq. (4-2) was tested in Column (2), yielding consistently negative coefficients, reinforcing the conclusion that DID effectively mitigates endogeneity concerns. Column (3) extends this analysis by examining

digitalization intensity through the triple interaction term $du_{it} \times dt_{it} \times digital$, with its negative coefficient demonstrating a dose-response relationship: stronger digitalization efforts amplify emission reductions. Columns (4)–(7) confirm analogous patterns for pollutant metrics, where heightened digitalization levels significantly lower both gas and wastewater emissions, validating robust environmental benefits of digital interventions in manufacturing sectors.

Critically, the DID framework necessitates validation of parallel trends between treatment and control groups prior to policy shocks. This study adopted a dynamic DID

specification, with visual evidence from Figures 2–3 and statistical tests confirming non-significant pre-treatment coefficients across comparison groups. Post-intervention coefficients attained significance at the 5 % level for $du \times after1$ (one-year lag), $du \times after2$ (two-year lag), and $du \times after3$ (beyond three years), while the contemporaneous term $du \times current$ remained insignificant. This temporal alignment reveals sustained emission reduction effects – specifically for CO₂ and SO₂ intensities – commencing one-year post-digital implementation and persisting thereafter.

Table 3

Differences-in-Differences (DID)

	CO2 emission			Air pollution		Water pollution	
	Inintenco2	Inintenco2	Inintenco2	SO2	NOX	COD	NH
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$du \times dt$	-1.0804*** (0.3844)	-0.5843** (0.2781)					
$du \times dt \times digit$			-0.4384*** (0.1659)	-0.0543** (0.0213)	-0.0518*** (0.0067)	-1.2579*** (0.2244)	-0.0319*** (0.0041)
Control variable	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes	yes	yes
N	18,594	18,470	18,470	18,470	16,545	16,545	16,545
R ²	0.018	0.164	0.164	0.147	0.786	0.556	0.777

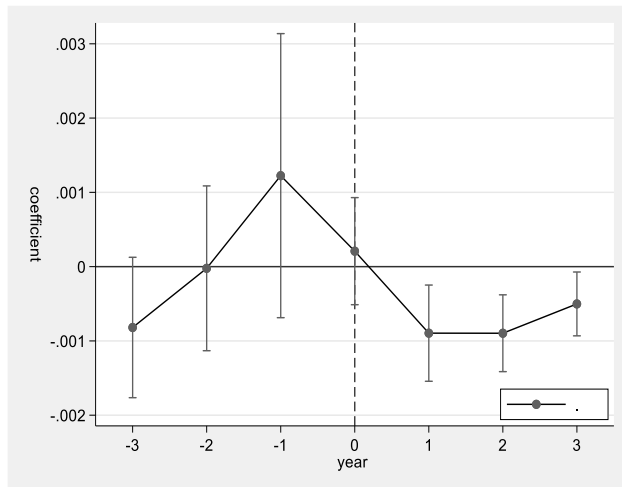


Figure 2. Dynamic Effect of Carbon Emission Reduction Brought by Enterprise Digitalization

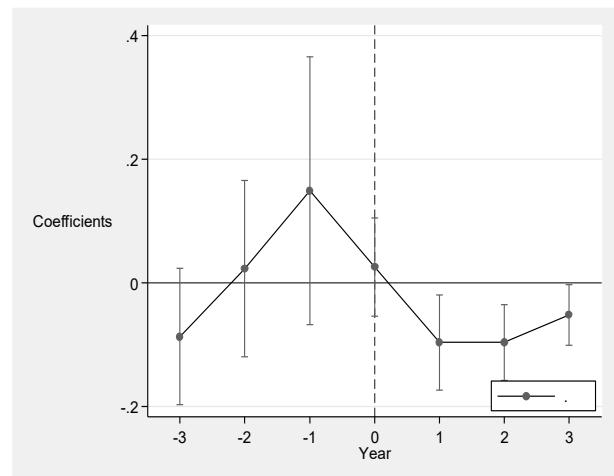


Figure 3. Dynamic Effect of Sulfur Dioxide Emission Reduction Brought by Enterprise Digitalization

Replace the Core Explanatory Variable

To ensure robustness, this study implemented multiple approaches to reconceptualize the core variable of enterprise digitalization. Drawing from Wu et al. (2021), alternative metrics were constructed based on keyword frequency ratios (designated as digital1 and digital2). Additionally, the digital_class index, derived from Wu et al. (2021)'s hierarchical classification framework, was adopted to evaluate digital maturity. Further granularity was achieved

by decomposing digitalization into five domain-specific dimensions, including artificial intelligence, followed by annual standardization and synthesis into a composite indicator (digital3). These methodological variations systematically addressed potential measurement biases inherent in textual analysis. The consistency of empirical outcomes across divergent operationalizations reinforced the reliability of the core findings, aligning with established robustness validation protocols in econometric research.

Table 4

Robustness Test: Replacing the Core Explanatory Variable

	(1)	(2)	(3)	(4)
	lnintenco2	lnintenco2	lnintenco2	lnintenco2
<i>digital1</i>	-0.4264** (0.1938)			
<i>digital2</i>		-3.3186** (1.5694)		
<i>digital_class</i>			-0.4241* (0.2414)	
<i>digital3</i>				-0.6284* (0.3363)
<i>Control variable</i>	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes
<i>N</i>	18,470	18,470	2,769	18,120
<i>R²</i>	0.164	0.164	0.445	0.147

Replace the Explained Variables

The study operationalizes CO₂ emission intensity through logarithmic transformations of emissions relative to operational income, supplemented by non-logarithmic metrics of output-normalized CO₂ emissions to address measurement discrepancies. Analytical outcomes for these variables are presented in designated columns of the primary results table. Beyond carbon metrics, the investigation incorporates multi-pollutant analysis encompassing chemical oxygen demand (COD) and ammonia nitrogen (NH) from industrial wastewater, alongside sulfur dioxide (SO₂) and nitrogen oxides (NO_x) from airborne emissions. These heterogeneous pollutants undergo systematic conversion into standardized emission equivalents using conversion coefficients prescribed by China's *Administrative Measures for Pollution Discharge Fee Collection Standards*, enabling cross-comparative quantification of environmental impacts.

The regulatory framework's equivalence values facilitate horizontal benchmarking of enterprise pollution levels, with resultant data visualized in subsequent table columns.

Complementing direct emission metrics, the analysis incorporates sewage charge (EFF) data as an institutional proxy reflecting regulatory penalties and energy conservation outcomes. This tripartite measurement strategy – encompassing carbon intensity, multi-pollutant standardization, and regulatory cost indicators – collectively demonstrates digitalization's capacity to mitigate diverse pollution vectors. Empirical validation through multivariate regression confirms the inverse relationship between digital adoption and emission intensities across all measured parameters, as demonstrated in columns (5) of Table 5. The methodological pluralism strengthens analytical robustness by triangulating emission reduction effects through operational, environmental, and regulatory lenses.

Table 5

Robustness Test: Replacing the Explained Variables

	intenco2	lnintenco2	Water pollution	Air pollution	EFF
	(1)	(2)	(3)	(4)	(5)
<i>digital</i>	-0.0523** (0.0224)	-8.2036*** (2.7766)	-0.0757*** (0.0083)	-0.0756*** (0.0083)	-0.5660** (0.2307)
<i>Control variable</i>	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes
<i>N</i>	18,470	18,470	16,545	16,545	18,470
<i>R²</i>	0.139	0.109	0.926	0.926	0.143

Eliminate the Influence of Strategic Behaviour of Enterprises

This study employs textual analysis of corporate annual reports to quantify enterprise digitalization levels, while acknowledging potential biases from strategic information disclosure practices. To address measurement validity concerns, multiple robustness checks were implemented. First, observations with zero digitalization values were

excluded to mitigate underreporting bias (Column 1). Second, potential overstatement of digital initiatives was addressed by eliminating samples exceeding the 80th percentile in disclosure residuals, countering conceptual speculation tendencies. Third, regulatory penalties for inadequate information disclosure prompted the exclusion of non-compliant firms. Fourth, the analysis retained only entities rated "excellent" or "good" in disclosure evaluations (Column 4). Fifth, temporal distortions from the 2015 stock

market crisis were controlled through period-specific sample exclusion, as market volatility might have incentivized artificial inflation of digitalization rhetoric (Column 5). Finally, manufacturing sector subsamples were analyzed separately given the industry's environmental significance. These methodological safeguards collectively strengthen the empirical foundation, with all robustness

checks confirming the core findings' stability (Table 6). The systematic approach addresses multiple dimensions of disclosure reliability while maintaining analytical rigor, particularly crucial when operationalizing textual indicators for complex organizational phenomena like digital transformation.

Table 6

Robustness Test: Eliminating the Strategic Behaviours of Enterprises

	lnintenco2	lnintenco2	lnintenco2	lnintenco2	lnintenco2	lnintenco2
	(1)	(2)	(3)	(4)	(5)	(6)
<i>digital</i>	-0.3893** (0.1685)	-0.8640*** (0.2499)	-0.3016* (0.1593)	-0.4903* (0.2531)	-0.3311** (0.1569)	-0.4501*** (0.1745)
<i>Control variable</i>	yes	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes	yes
<i>N</i>	16,765	14,723	10,868	9,495	16,556	14,440
<i>R²</i>	0.214	0.203	0.299	0.144	0.181	0.157

Mechanism Analysis

Prior empirical evidence robustly endorses the idea that digitalization is a crucial element in diminishing emissions within enterprises, thus improving the GLCT. The findings demonstrate a clear and substantial correlation between digitalization and the reduction of emissions. This paper discusses the green and low-carbon transformation (GLCT) mechanism of enterprise digitalization, grounded in prior theoretical derivation, from the perspectives of enterprise innovation, efficiency promotion, improvement of operating environment and optimization of internal structure.

Innovation Mechanism of Digitalization

This study highlights the pivotal role of digital transformation in advancing corporate green technological innovation. By fostering breakthroughs in clean technologies, digitalization improves the efficacy of carbon dioxide management and conversion processes, thereby reducing enterprises' carbon emission intensity. To quantify

green innovation outcomes, the logarithmic value of green patent counts (*lnGPat*) was adopted as a proxy measure. Empirical evidence further reveals that digital adoption stimulates R&D expenditure, creating a synergistic effect on emission mitigation. Supplementary innovation metrics included R&D intensity (RD, calculated as R&D investment-to-revenue ratio) and total patent output (lnPat), with detailed classifications distinguishing utility patents (*lnipat*) from design patents (*lnides*). Collaborative innovation dynamics were examined through separate analyses of independently developed patents (*lnind*) versus jointly filed patents (*lnunit*). Regression analyses (Table 7) substantiate Hypothesis 2, demonstrating statistically significant positive coefficients for digitalization variables. These findings confirm that technological innovation serves as a crucial mediator in emission reduction, validating its indispensability for achieving carbon neutrality objectives. The results underscore digitalization's dual capacity to enhance corporate inventive capabilities while driving environmentally sustainable industrial practices.

Table 7

Mechanism Analysis: Enhancing the Enterprise Innovation Capability

	lnGpat	RD	lnPat	Patient applied			
	(1)	(2)	(3)	lnipat	lnides	lnind	lnunit
<i>digital</i>	0.0199** (0.0084)	0.0498* (0.0297)	0.0350*** (0.0135)	0.0323*** (0.0110)	0.0344*** (0.0127)	0.0264* (0.0135)	0.0251*** (0.0095)
<i>Control variables</i>	yes	yes	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>N</i>	17,202	12,623	18,466	18,466	18,466	18,466	18,466
<i>R²</i>	0.746	0.852	0.783	0.770	0.768	0.766	0.671

Efficiency Promotion Mechanism of Digitalization

Digital transformation serves as a critical catalyst for improving industrial productivity and sustainable resource

management. This study quantifies production efficiency through total factor productivity (TFP) metrics calculated via Olley-Pakes (OP) and Levinsohn-Petrin (LP) methodologies,

while employing energy consumption intensity as an inverse proxy for energy efficiency.³ Empirical analysis demonstrates that digital integration significantly enhances TFP levels (Table 8, Columns 1–2), confirming its capacity to optimize production processes and reduce resource misallocation. Concurrently, digital adoption drives measurable improvements in energy utilization, evidenced by decreased standard coal consumption per revenue unit (Column 3). Extended evaluations across fossil fuel dependency, aggregate energy use, and water consumption metrics (Columns 4–7) further reveal consistent reductions

in resource inputs per economic output. These findings collectively illustrate digitalization's dual capacity to boost operational efficiency while advancing environmental sustainability. The results underscore digital technologies as essential tools for achieving energy intensity reduction targets, particularly through enhanced production system optimization and intelligent energy management capabilities. This multi-dimensional analysis establishes digital transformation as a fundamental mechanism for reconciling industrial productivity with low-carbon development objectives.

Table 8

Mechanism Analysis: Production Efficiency Promotion

	Total Factor Productivity		Energy efficiency				
	TFP OP	TFP LP	Coal	Fossil	Total	Electricity	Water
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>digital</i>	0.0124** (0.0055)	0.0365*** (0.0060)	-0.0028*** (0.0004)	-0.0049*** (0.0006)	-0.0370*** (0.0047)	-0.0229*** (0.0030)	-0.0023*** (0.0003)
<i>Control variable</i>	yes	yes	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>N</i>	18,033	15,954	16,542	16,542	16,542	16,542	16,542
<i>R²</i>	0.872	0.934	0.816	0.818	0.817	0.816	0.816

Improvement of Operating Environment

The internet has transformed information sharing and access, allowing for the immediate distribution of remote information. This breakthrough has substantially impacted information accessibility. The ratio (ASY1, ASY2) of the absolute value of accruing assets managed by listed companies to total assets is used to characterize the information asymmetry (Ma *et al.*, 2021). Furthermore, digitalization has established a new information paradigm for financial sector, expedited digital finance, reduced financing threshold, and mitigated enterprise financing constraints. Alleviation of enterprise financing constraints can positively impact their capacity to invest in emission reduction technology and upgrade their industrial structure. This paper used the SA indicator and KZ indicator to evaluate the financing constraints faced by enterprises. Through digitalization, enterprises can obtain market and user information via various channels, improve the adaptability of production interconnections among industrial enterprises, and diminish customer concentration.

Moreover, enterprises can minimize resource waste and pollution resulting from excessive production, while accelerating the low-carbon manufacturing. The ratio of sales amount from the top five users to the total sales amount (CR5) and its quadratic sum (CR5_sq) were taken as the measures of customer concentration. The estimation is presented in Columns (5) – (6) of Table 9.

The regression results in Table 9 demonstrate that digitalization can substantially mitigate information asymmetry. The regression results indicate that enterprise digitalization significantly alleviate financing constraints, thereby providing adequate financial support for the GLCT. The estimation coefficient of digital in column (5) is obviously negative, indicating that enterprise digitalization facilitates organizations in forming large cooperative relationships with numerous partners rather than being constrained to a small number of partners. Given the circumstances, product sales accuracy will be enhanced, resource waste will be diminished, and carbon emissions will be further decreased.

³ For energy consumption rate, the ratio of coal consumption (Coal) and other fossil energy consumption (Fossil) of enterprises to the total output value of enterprises was taken as the proxy indicator of energy consumption rate. The greater the value, the lower the energy utilization rate. Conversely, the smaller the value, the higher the energy utilization rate. On this basis, according to the research of the Center for Higher Education Development of Xiamen University, all energy consumption was converted into standard coal to calculate the total energy consumption per unit of operating income (Total). In addition, considering that thermal

power generation was still the main source of electricity in China and the use of electricity in the daily production process of enterprises would also lead to indirect carbon emissions, the electricity consumption per unit of operating income (Electricity) of enterprises was further included in the regression to investigate the energy-saving effect of digitalization. Finally, the water consumption per unit of operating income (water) was used as an indicator to measure the lean production of enterprises, and the influence of enterprise digitalization on the enterprise's production mode was verified.

Table 9

Mechanism Analysis: Improvement of Operating Environment

	Information asymmetry		Financial constraints		Customer Concentration	
	ASY1	ASY2	SA	KZ	CR5	CR5_sq
	(1)	(2)	(3)	(4)	(5)	(6)
<i>digital</i>	-0.0221*** (0.0045)	-0.0262*** (0.0050)	-0.0044*** (0.0011)	-0.0297* (0.0171)	-0.0052*** (0.0018)	-0.0064*** (0.0018)
<i>Control variable</i>	yes	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes	yes
<i>N</i>	18,145	18,145	18,466	15,772	16,537	
<i>R²</i>	0.590	0.699	0.963	0.849	0.462	

Optimization of Production and Operating Structure

Theoretical analysis indicates that digitalization can reduce carbon and pollutant emission by facilitating the structural optimization of production process. This article uses the operating cost ratio (operating cost / operating income) as a mediating variable to represent the optimization of enterprise structure, as illustrated in Column (1) of Table 10. The significantly negative estimation coefficient of digital shows that enterprise digitalization can obviously reduce enterprises' operating cost. Enterprise digitalization enhances the optimization of human capital and provides intellectual support for carbon emission reduction in operational processes. The human capital structure of enterprises was measured using the proportion of employees with a bachelor's degree or above (*HR*). The estimation in Column (2) indicates the digital technology can help company to enhance the human capital level of enterprises. Additionally, enterprise digitalization promotes the transformation of production organizational forms, enhances specialization in the division of labor, and ultimately reduces the enterprises carbon emission intensity. Besides, the vertical integration degree (VAS) of enterprises was measured using the Value Added to Scales, and the degree of specialization (VSI) was defined as the contrary indicator. The specific calculation formula is as follows:

$$VAS = \frac{\text{Added value} - \text{net profit after tax} + \text{normal profit}}{\text{Main operating income} - \text{net profit after tax} + \text{normal profit} + \text{added value} - \text{net profit after tax} + \text{net assets} \times \text{average return on equity}}$$

The VAS value has an inverse correlation with the specialization level of companies. Using this indicator, the inverse indicator VSI may be calculated, that is, $VSI = 1 - VAS$. The extent of specialization was measured with the Value Added to Scales (VAS), with a greater VSI value indicating a higher level of specialization. In Column (3), the positive regression coefficient of digital suggests that the specialization of enterprises is significantly enhanced by the implementation of enterprise digitalization. To measure the specialization of enterprises, the natural logarithm of highly cited invention patents number of company in the current year (incited) was used as a proxy variable.⁴ The regression coefficients of digital in Columns (4)-(6) of Table 10 are all significantly positive, indicating that digitalization can positively impact the specialized production. Additionally, the internal control level, namely the "DIB internal control index of listed companies in China," was applied to assess the internal control level (*InnCt*). The index covers multiple facets, including control activities and internal oversight. The results in Table 10 indicate that enterprise digitalization can improve the internal control level, which benefits for the GLCT of enterprises.

Table 10

Mechanism Analysis: Optimization of Production and Operating Structure

	<i>Cost</i>	<i>HR</i>	<i>Specialization</i>				<i>Internal Control</i>
			<i>VSI</i>	<i>Lncited1</i>	<i>Lncited5</i>	<i>Lncited10</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>digital</i>	-0.0053* (0.0029)	0.2722*** (0.1032)	0.0373*** (0.0106)	0.0123** (0.0061)	0.0267*** (0.0092)	0.0319*** (0.0101)	0.0598*** (0.0169)
<i>Control variable</i>	yes	yes	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes	yes	yes
<i>N</i>	18,193	13,277	11,249	18,466	18,466	18,466	16,928
<i>R²</i>	0.277	0.887	0.730	0.729	0.797	0.832	0.829

⁴ Patents achieving top 1 % industry citation frequency (Lncited1) are classified as highly cited, indicating cutting-edge technological innovation.

Alternative thresholds of top 5 % (Lncited5) and 10 % (Lncited10) citation rankings were adopted for robustness analysis.

Heterogeneity Analysis

Due to the distinct characteristics of various industries, the impact of enterprise digitalization on carbon reduction may have asymmetric results, and evaluating such cases is beneficial for developing appropriate regulatory strategies. This study classifies the samples for discussion based on the nature of property rights, industrial heterogeneity, regional environmental regulation intensity and digital technology heterogeneity.

Heterogeneity of the Nature of Enterprise Property Rights

Drawing on China's unique institutional context where state-owned enterprises (SOEs) operate under distinct regulatory frameworks and social responsibilities compared to private counterparts, this study conducts ownership-based heterogeneity analysis. By categorizing firms into SOEs and non-SOEs and introducing an interaction term ($digital \times SOE$), we systematically examine how digital transformation differentially impacts green and low-carbon transition (GLCT) across ownership types.

The baseline regression reveals an insignificant coefficient (Column 1) for the interaction term at 1 % level, indicating no statistically discernible difference in digitalization's carbon intensity reduction effects between ownership types. This parity may stem from the non-mandatory nature of corporate carbon disclosure systems, which fail to incentivize differentiated emission reduction strategies across ownership structures. However, columns (2)–(5) demonstrate statistically negative coefficients for the interaction term at 10 % significance level when measuring wastewater (COD) and air pollutant (SO₂, NO_x) emission intensities. These findings suggest SOEs exhibit superior performance in digital-driven pollution mitigation, potentially attributable to their institutional characteristics: reduced profit sensitivity enables stricter compliance with national environmental mandates, including proactive phasing-out of obsolete equipment and upgrading pollution control facilities in alignment with administrative directives. The evidence implies SOEs' unique position as policy implementers amplifies digitalization's environmental benefits in specific emission categories despite equivalent carbon reduction outcomes across ownership types.

Table 11

Heterogeneity of the Nature of Enterprise Property Rights

	Co2 emission	Air pollution		Water pollution	
	Inintenco2	SO2	NOX	COD	NH
	(1)	(2)	(3)	(4)	(5)
<i>digital</i>	-0.0731 (0.1700)	-0.0040 (0.0173)	-0.0087 (0.0091)	-0.3460 (0.3002)	-0.0060 (0.0054)
<i>digital</i> × <i>SOE</i>	-0.2340 (0.1968)	-0.0360* (0.0217)	-0.0489*** (0.0125)	-0.9734** (0.4510)	-0.0272*** (0.0077)
<i>Control variable</i>	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes
<i>N</i>	12,887	12,887	11,450	11,450	11,450
<i>R</i> ²	0.294	0.273	0.863	0.631	0.849

Industry Heterogeneity

The influence of digitalization on enterprise green and low-carbon transformation (GLCT) demonstrates significant heterogeneity contingent upon organizational characteristics. Enterprises in highly competitive industries encounter intensified challenges in establishing market advantages and sustaining profitability. Digital adoption stimulates technological innovation and elevates product competitiveness while optimizing resource allocation efficiency, thereby facilitating energy conservation and emission mitigation. This study utilizes the Herfindahl-Hirschman Index (HHI) to categorize industries into high- and low-competition cohorts based on median HHI thresholds. An interaction term ($digit \times HHI$) was incorporated to assess differential GLCT outcomes. Empirical results (Table 12) reveal consistently negative

coefficients for digitalization, confirming its efficacy in reducing emissions. Notably, interaction term coefficients exhibit significant negativity across specifications (excluding Column 4), indicating that competitive market environments amplify digitalization's emission-reduction potential. Firms in high-competition sectors achieve more pronounced declines in carbon intensity and pollutant discharge due to heightened operational pressures and innovation-driven adaptability. These findings underscore that market competition acts as a catalyst, incentivizing enterprises to strategically deploy digital tools for process optimization and sustainable practices. Consequently, competitive dynamics enhance the alignment between digital transformation and environmental objectives, positioning industry structure as a critical moderator in GLCT pathways.

Table 12

Heterogeneity of Industry Competition

	CO2 emission	Air pollution		Water pollution	
	lnintenco2	SO2	NOX	COD	NH
	(1)	(2)	(3)	(4)	(5)
<i>digital</i>	-0.2626** (0.1250)	-0.0339** (0.0139)	-0.0522*** (0.0066)	-1.1978*** (0.2427)	-0.0321*** (0.0041)
<i>digit_HHI</i>	-0.2721** (0.1309)	-0.0315** (0.0141)	-0.0145** (0.0057)	0.2148 (0.2297)	-0.0084** (0.0035)
<i>Control variable</i>	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes
<i>N</i>	18,466	18,466	16,542	16,542	16,542
<i>R²</i>	0.189	0.176	0.811	0.575	0.802

Heterogeneity of Environmental Regulation Intensity

This study examines how regional environmental regulation intensity moderates enterprise digitalization's effect on GLCT. Provincial-level environmental regulation data was utilized to categorize firms into high-regulation (regulation=1) and low-regulation (regulation=0) groups using median intensity thresholds. An interaction term (*digit×reg*) was constructed to assess regulatory heterogeneity. Results in Table 13 reveal that digitalization coefficients remain significantly negative across groups,

confirming its consistent GLCT-promoting effect. However, the statistically insignificant interaction term coefficients indicate no discernible heterogeneity in digitalization's emission-reduction efficacy between regions with differing regulatory intensities. This suggests environmental regulation strength neither amplifies nor diminishes enterprises' capacity to leverage digital transformation for sustainable transition, highlighting digitalization's inherent potential as an independent driver of low-carbon development across regulatory contexts.

Table 13

Heterogeneity of Environmental Regulation Intensity

	CO2 emission	Air pollution		Water pollution	
	lnintenco2	SO2	NOX	COD	NH
	(1)	(2)	(3)	(4)	(5)
<i>digital</i>	-0.3680*** (0.1306)	-0.0462*** (0.0156)	-0.0468*** (0.0060)	-1.1423*** (0.2329)	-0.0303*** (0.0037)
<i>digit_reg</i>	-0.0395 (0.0876)	-0.0045 (0.0106)	0.0025 (0.0044)	0.0854 (0.1972)	0.0040 (0.0027)
<i>Control variable</i>	yes	yes	yes	yes	yes
<i>Industry FE</i>	yes	yes	yes	yes	yes
<i>City FE</i>	yes	yes	yes	yes	yes
<i>Firm FE</i>	yes	yes	yes	yes	yes
<i>Year FE</i>	yes	yes	yes	yes	yes
<i>N</i>	18,466	18,466	16,542	16,542	16,542
<i>R²</i>	0.189	0.175	0.811	0.575	0.802

Digital Technology Heterogeneity

The effects of different digital technologies on carbon emission reduction potentially vary. Following Wu et al. (2021), this study categorizes digital indicators into two tiers: the foundational technical tier (encompassing AI, blockchain [BD], cloud computing [CC], and big data [BT]) and the practical application tier, with a focus on the latter. Empirical findings reveal distinct impacts across technologies, as

detailed in Table 14. AI, CC, BT, and BD exhibit differing roles in reducing corporate carbon emissions. Specifically, AI, CC, and BT demonstrate significant positive effects, whereas BD shows a negative yet statistically insignificant association with emission reduction. These results underscore the nuanced influence of digital tools, emphasizing the need for differentiated strategies in leveraging technology for green transformation.⁵

⁵ The regression results of wastewater and waste gas are similar, which are not listed here due to limited space.

Table 14

Digital Technology Heterogeneity					
	lnintenco2	lnintenco2	lnintenco2	lnintenco2	lnintenco2
	(1)	(2)	(3)	(4)	(5)
AI	-0.5014** (0.2299)				
DT		-0.5115** (0.2478)			
CC			-0.3601** (0.1701)		
BC				-0.9640 (0.6055)	
ADT					-0.4088** (0.1910)
Control variable	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
City FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
N	18,470	18,470	18,470	18,470	18,470
R ²	0.163	0.164	0.163	0.163	0.164

Conclusion

This study investigates the role of enterprise digitalization in advancing green and low-carbon transformation (GLCT) among Chinese A-share listed firms (2008–2020), emphasizing its mechanisms and heterogeneous impacts. Key findings demonstrate that digitalization significantly drives GLCT by reducing carbon dioxide and pollutant emissions. Robustness checks, including endogenous treatment, difference-in-differences (DID) analysis, and variable substitution, confirm the validity of this conclusion. Mechanism analysis identifies four critical pathways: technological innovation enhances clean energy adoption and carbon conversion efficiency; operational efficiency improvements optimize energy use; environmental upgrades minimize production waste; and structural adjustments streamline resource allocation. Notably, digital tools such as AI and big data demonstrate strong emission-reduction effects, though blockchain technology shows limited efficacy. Heterogeneity tests reveal that state-owned enterprises (SOEs) and firms in highly competitive industries benefit disproportionately from digitalization due to resource advantages and market pressures. However, regional variations in environmental regulation intensity yield no significant differences in GLCT outcomes, suggesting uniform policy applicability. These insights underscore digitalization's dual role in fostering sustainable practices and aligning with China's carbon neutrality goals, offering actionable strategies for sector-specific decarbonization.

The findings of this study yield several actionable policy recommendations. First, governments should prioritize advancing digital infrastructure and establishing specialized public service platforms. Regional authorities could allocate dedicated funds to support corporate digital transformation, tailored to local economic conditions and technological readiness. Such initiatives may include creating digital transformation hubs to provide technical guidance, financial subsidies, and collaborative networks, effectively addressing enterprises' operational constraints and risk aversion during technological adoption. Second, enterprises must strategically integrate digital technologies across production processes to drive systemic innovation. This involves optimizing resource allocation through smart manufacturing systems and data analytics, thereby reducing energy intensity while enhancing production flexibility and operational efficiency. Third, policymakers should complement digital transformation efforts with complementary institutional frameworks. Strengthening market competition mechanisms and implementing rigorous environmental compliance audits could incentivize green production practices. Concurrently, targeted dissemination of environmental regulations and sustainability benchmarks through industry associations would cultivate corporate environmental stewardship, amplifying the green low-carbon transition (GLCT) effects of digitalization.

Appendix

Descriptive statistics of the main variables in this paper are presented in Table 1.

Appendix Table 1

Descriptive Statistics					
Variable	N	Mean	S.D.	Min	Max
lnintenco2	18594	3.3148	9.2005	0.0000	766.4252
SO2	18594	0.3358	1.1143	0.0000	100.6753
NOX	16897	0.6432	0.7239	0.0039	8.6466
COD	16897	14.7326	21.2207	0.0007	307.6471
NH	16897	0.3795	0.4299	0.0024	4.9396

Variable	N	Mean	S.D.	Min	Max
digit	18594	1.2154	1.0850	0.0000	4.6728
top1	18594	0.3667	0.1487	.0957	0.7561
indep	18594	0.3715	0.0527	.3077	0.5714
board	18594	2.154	0.1957	1.6094	2.7081
listdt	18594	1.9542	0.9347	0.0000	3.2189
roe	18594	0.0688	0.1175	-0.6275	0.4157
tangibility	18594	0.2924	0.1884	0.0034	0.8007
growth	18594	0.1553	0.3117	-0.5622	1.7627
cf	18594	0.0468	0.0711	-0.1802	0.2507
lev	18594	0.4319	0.2116	0.0483	0.9865
gprofit	18594	0.278	0.1671	-0.0176	0.7990

The above table presents the descriptive statistical results of main variables. It can be seen that the average annual carbon emission intensity of listed companies is 3.3148. The maximum and minimum values are 0 and 766.4252 respectively, which indicates that the carbon emission intensities of different enterprises are quite different. The average value of digital transformation (digital) is 1.085, the maximum value is 4.6728, and the minimum value is 0, which are basically consistent with the calculation results of Wu et al. (2021). It demonstrates that there is a big gap among enterprises in their emphasis on digital transformation and their transformation progress. Besides, there is a phenomenon that some leading enterprises have been in the transformation process, while some enterprises have not yet chosen to make transformation.

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