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Effects and Mechanisms of Digital Transformation on the Carbon Emission Performance of Textile Enterprises

Tao Ma

School of Management, Shanghai University of Engineering Science, Shanghai 201620, China

ziliaozhuanyong9@163.com

Article

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ABSTRACT

Against the backdrop of global carbon neutrality goals, the textile industry, a labor-intensive and high-emission sector, faces urgent challenges in its green transition. However, empirical research examining how digital transformation (DT) drives carbon emission performance (CEP) in labor-intensive, low-innovation sectors such as textiles remains limited. Addressing this gap, this study applies the resource-based view (RBV) to explore whether green technological innovation (GTI) mediates the DT-CEP relationship in textile enterprises. The study utilizes panel data from 187 Chinese A-share listed firms (2013–2022) and employs fixed-effects regression with bootstrapping for mediation analysis. The results reveal three main findings. First, DT, measured by heterogeneous resources (digital technology assets and digital talent), has a positive effect on GTI. Among these resources, digital talent plays a stronger role in driving innovation than technology assets. Second, GTI, particularly process innovation (e.g., energy-efficient dyeing), significantly improves CEP. Third, GTI mediates 7.9%–16.5% of the DT-CEP relationship, providing new evidence on the importance of innovation for DT-driven carbon reduction in labor-intensive sectors, particularly among leading textile firms.

This study extends RBV beyond capital-intensive manufacturing by demonstrating that heterogeneous digital resources can build green capabilities even in low-innovation firms. For global practice, the findings highlight digital talent development as key to green transitions in the textile industry, offering actionable insights for firms, policymakers, and international organizations aligned with the UN Sustainable Development Goals. This research advances cross-sectoral RBV application and provides a benchmark for DT-innovation-CEP studies in emerging economies.

KEYWORDS

textile enterprises, digital transformation, green technological innovation, carbon emission performance, resource-based view

INTRODUCTION

The Paris Agreement (UNFCCC, 2015) has intensified global efforts toward carbon neutrality, placing industries with high environmental footprints under increasing scrutiny. The textile sector is a significant contributor to global environmental challenges, accounting for up to 8% of carbon emissions and 20% of industrial water pollution (UNEP, 2022). Major textile-producing nations such as China (50% of global output), India (15%), and Bangladesh (8%) are now aligning with international climate goals. In this context, digital transformation has emerged as a pivotal tool for achieving decarbonization within the sector. For instance, the EU's Circular Economy Action Plan (2020) mandates digital traceability for textiles to reduce waste, while the OECD (2023) highlights digital technologies as key to optimizing resource use in labor-intensive sectors. Despite this global momentum, empirical research on how digital transformation affects carbon emission performance in textile enterprises remains limited. Most studies focus on energy-intensive industries (e.g., steel, chemicals) or high-tech manufacturing, where digital tools such as IoT and AI deliver clear emission reductions. In contrast, the textile industry, characterized by fragmented supply chains, low R&D investment (1%–2% of revenue; WTO, 2023), and reliance on traditional processes, faces unique barriers to translating digitalization into green outcomes. This relatively low R&D investment underscores why the textile industry is often characterized as a low-innovation sector. This gap is critical: textile exports drive 5%–10% of GDP in many developing economies, making its green transition vital to both environmental sustainability and economic resilience.

Against this backdrop, the core research question of this study is: Does green technological innovation (measured by R&D investment in green processes and green product development) mediate the relationship between digital transformation and carbon emission performance in textile enterprises, and what is the magnitude of this mediating effect? This question addresses two unresolved issues in international research. First, does the innovation-mediated pathway, which is well supported by existing literature in capital-intensive industries, also hold true for labor-intensive textile enterprises, where innovation capacity is constrained? Second, how do heterogeneous digital resources (e.g., digital technology assets vs. digital talent) differentially influence green innovation and carbon performance? For example, while digital technology assets (e.g., IoT sensors) may optimize production in real time, digital talent (e.g., data scientists) could drive longer-term green R&D. However, few studies have disentangled these mechanisms in the textile context.

International scholarship on digital transformation and carbon performance has converged around three themes. First, scholars apply the resource-based view (RBV) to frame digitalization as a source of heterogeneous, non-imitable resources that enhance environmental capabilities [1]. For example, Yang et al. demonstrate that digital assets reduce carbon intensity in Chinese listed firms by improving resource allocation [2]. Second, the innovation-mediated pathway: studies show digitalization stimulates green technological innovation, defined as R&D in green processes (e.g., energy-efficient dyeing) and products (e.g., recycled textiles), which in turn boosts carbon performance. Green innovation mediates 30% of the digital-carbon relationship in Chinese firms [3]. Third, industry heterogeneity: AI increases emissions in energy-intensive sectors but reduces them in light manufacturing [4], while Zhao et al. link construction firms' digital transformation to emission reductions via process optimization [5]. However, three key gaps remain. First, sectoral focus: nearly all studies exclude textiles, where low digital penetration and weak innovation capacity may alter the digital-green link. Second, variable granularity: most studies measure digital transformation as an aggregate index, failing to distinguish between resources that drive different types of green innovation. Third, mediation magnitude: the precise contribution of green innovation in textile firms, in which R&D is limited, remains unknown.

This study advances both theory and practice. Theoretically, it extends the RBV by testing its applicability to labor-intensive, low-innovation sectors. By decomposing digital transformation into heterogeneous resources (talent vs. assets) and quantifying their mediating effects via green innovation, we address the gap in sector-specific RBV applications. Practically, the findings will help textile firms prioritize investments: if digital talent has a larger mediating effect than technology assets, firms should focus on upskilling rather than hardware purchases. For policymakers, results will inform targeted policies, such as tax incentives for green R&D in digitalized textile firms or subsidies for digital talent training, aligning with UN Sustainable Development Goal (SDG) 12 (responsible consumption) and the G20's sustainable manufacturing priorities. The framework also supports cross-national comparisons, as textiles in India and Bangladesh face similar digital-green challenges.

Guided by the RBV, we construct an analytical framework in which heterogeneous digital resources (independent variables: digital technology assets as a percentage of total assets, digital talent as a percentage of total employees) influence carbon emission performance (dependent variables: carbon efficiency [output value per ton of CO_2], carbon footprint compliance rate) via green technological innovation (mediators: green process R&D intensity, green product project count). We use unbalanced panel data from 187 Chinese A-share listed textile enterprises (2013–2022), selected for their representation of the global supply chain. Data sources include the China Stock Market & Accounting Research Database (CSMAR), China Emission Accounts and Datasets (CEADs), and company reports. To test mediation, we follow Baron and Kenny's framework augmented with bootstrapping (5,000 iterations) to address endogeneity [6,7]. We control for firm-level (firm size, financial leverage), ownership (state-owned vs. private), and regional (GDP per capita, environmental regulation) variables to isolate digital transformation's effects. Specifically, the environmental regulation variable (Env_{Reg}) captures the intensity of provincial/municipal environmental policy enforcement, helping to control for the confounding effect of top-down mandatory compliance pressure on CEP.

This study contributes to the literature in four ways: first, it tests RBV's applicability to labor-intensive textiles, a sector where traditional innovation capacity is constrained, thereby extending the theory's boundary conditions; second, it decomposes DT into technology and talent dimensions to identify their differential impacts—specifically, the differential impacts of heterogeneous digital resources (i.e., digital technology assets vs. digital talent) on green technology innovation. In textile enterprises, digital talent exerts a stronger positive effect on green technological innovation than digital technology assets do. Third, it quantifies the mediating effect of GTI, providing a benchmark for low-innovation industries. Fourth, by focusing on the specific context of the textile industry, it provides evidence from a representative sample of leading Chinese textile firms.

LITERATURE REVIEW

The literature on digital transformation (DT), green technological innovation (GTI), and carbon emission performance (CEP) is primarily rooted in the RBV, which emphasizes that heterogeneous, non-imitable resources drive sustainable competitive advantages [8]. Recent studies have confirmed that DT, as an emerging intangible resource, enhances firms' environmental capabilities by integrating digital technologies and data-driven human capital into operations. For example, Yang et al. found that DT reduces carbon intensity by improving resource allocation in Chinese listed firms, while Deng et al. revealed that digitalization enhances energy efficiency and environmental performance through innovation upgrading [1,2]. However, these studies mainly focus on capital-intensive sectors, leaving labor-intensive industries, such as textiles, largely underexplored.

A second strand of research investigates the mediating role of GTI in the DT-CEP relationship. GTI represents a firm's ability to integrate digital and environmental capabilities to create low-carbon technologies and products. Empirical evidence suggests that DT stimulates GTI by enabling data-driven R&D and efficient production processes, which subsequently improve CEP. For instance, Hou et al. incorporate a heterogeneous threshold of green technology innovation into the influential mechanism to figure out whether the digital economy can effectively reduce regional carbon emissions [3]. However, these findings may not generalize to labor-intensive sectors, where innovation investment is typically below 2% of revenue (WTO, 2023), limiting the potential for green R&D. Moreover, many existing studies rely on aggregate patent indicators that fail to capture sector-specific GTI activities such as energy-efficient dyeing or recycled textile projects [4,5].

A third body of literature examines resource heterogeneity within DT. Scholars have begun to differentiate between digital technology assets (hardware and software infrastructure) and digital talent (employees with digital and analytical capabilities). Ma and Tao argued that management myopia weakens the emission-reduction effects of DT unless firms invest in digital talent capable of long-term green innovation [9]. Ding and Wang further demonstrated that subsidies for digital talent generate stronger environmental outcomes than subsidies for hardware [10]. Yet, no studies have explicitly compared the relative effects of digital talent and technology assets on GTI and CEP in the textile sector, which is characterized by low digital skill penetration (only 3% of employees possess digital skills; China Textile Industry Federation, 2023).

In summary, existing research offers three key insights but also reveals three unresolved gaps. First, RBV provides a solid framework to link DT and CEP through heterogeneous resources, yet its applicability to labor-intensive sectors such as textiles remains untested. Second, empirical studies have verified GTI's mediating role in manufacturing and construction but rarely in low-innovation industries. Third, few studies have disentangled heterogeneous DT resources to clarify which type (technology or talent) contributes more to GTI and CEP. Addressing these gaps, this study applies RBV to the textile industry, decomposes DT into two resource dimensions, and tests the mediating role of GTI using sector-specific indicators. This approach advances both theory and practice by extending RBV's validity and offering actionable insights for the green transition of labor-intensive enterprises.

THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

Theoretical Basis

In 1984, Birger Wernerfelt explicitly coined RBV for the first time, advocating that a firm's resource portfolio should serve as the starting point for strategic analysis. In 1991, Jay B. Barney systematically elaborated on the four key attributes that resources must possess to generate sustained competitive advantage: value, rarity, inimitability, and non-substitutability—collectively known as the renowned VRIN framework.

The VRIN framework is the most operational analytical tool within the RBV paradigm. It provides a systematic criterion to assess whether a specific resource or capability of a firm has the potential to become a source of sustained competitive advantage (SCA). VRIN is an acronym derived from the four evaluative dimensions: value, rarity, inimitability, and non-substitutability. Only when a resource or capability satisfies all four criteria can it endow a firm with sustained competitive advantage. Based on RBV theory, this paper operationalizes the independent variable DT into two types of heterogeneous resources: digital technology assets and digital talent.

The RBV provides the theoretical foundation for this study. RBV offers a parsimonious, logic-driven framework for explaining how heterogeneous organizational resources drive environmental capabilities and outcomes, specifically the relationship between DT, GTI, and CEP that this research explores. RBV posits that firms gain competitive advantages by leveraging valuable, rare, inimitable, and non-substitutable (VRIN) resources to develop dynamic capabilities [8]. For textile enterprises, which are labor-intensive firms with very limited innovation capacity (e.g., R&D spending only 1%–2% of revenue), far lower than that of industries such as electronics and pharmaceuticals, DT represents a critical source of VRIN resources that can overcome barriers to green transition. Digital technology assets are valuable (they optimize production efficiency and reduce waste) and rare (not all textile firms, especially small and medium-sized enterprises (SMEs), can afford IoT/AI infrastructure), but they are relatively imitable (competitors can purchase similar equipment). Digital talent is more inimitable and non-substitutable because human capital with combined expertise in data analytics and green R&D is extremely scarce in an industry where only 3% of employees possess digital skills. This scarcity creates a sustainable competitive advantage that cannot be easily replicated. Unlike capital-intensive sectors (e.g., steel, construction), where RBV has been extensively validated, the applicability of

RBV to textiles remains untested [1,5]. This study addresses that gap by applying RBV to a labor-intensive context, where DT resources (rather than physical capital) may be the key to building GTI capabilities and improving CEP.

RBV's logic centers on two interrelated components: resources (tangible or intangible assets) and capabilities (processes that integrate resources to create value). For this study:

(1) DT is operationalized as two heterogeneous resources: digital technology assets (e.g., IoT sensors, AI-driven production systems, measured as a percentage of total assets) and digital talent (e.g., data scientists, digital process managers, measured as a percentage of total employees). These resources exhibit the VRIN characteristics of RBV. Digital technology assets are valuable (optimize production efficiency) and rare (not all textile firms can afford IoT infrastructure), whereas digital talent is more inimitable and non-substitutable (human capital with expertise in data analysis and green R&D is scarce, particularly in a sector where only 3% of employees have digital skills; China Textile Industry Federation, 2023).

(2) GTI is a dynamic capability developed by integrating DT resources. GTI is defined here as green process R&D intensity (investment in energy-efficient dyeing or water recycling) and green product project count (development of recycled textiles or low-carbon fabrics). Per RBV, DT resources enable firms to collect and analyze production data (via digital technology) and translate that data into innovative green solutions (via digital talent), thereby building a capability that competitors cannot easily copy. For example, digital talent can analyze production data (such as energy consumption during dyeing; energy consumption and water consumption data of dyeing equipment) and identify inefficient links in the production process to optimize process parameters (e.g., temperature, dye concentration, and process duration), enabling the adoption of energy-efficient dyeing techniques to achieve green innovation. This explains why digital talent exerts a stronger effect on GTI than technology assets alone: talent provides the critical capability to bridge digital insights and physical process improvements. The key insight is that digital talent possesses the unique capability to translate abstract data patterns into tangible, implementable engineering solutions.

(3) CEP is the environmental outcome of GTI, measured as carbon efficiency (output value per ton of CO_2) and carbon footprint compliance rate (adherence to regional/national emission standards). RBV predicts that GTI, rooted in VRIN DT resources, will drive superior CEP by reducing energy waste, improving resource allocation, and meeting regulatory demands.

While RBV was originally developed and validated primarily in capital-intensive manufacturing contexts (e.g., Deng et al., 2023; Zhao et al., 2025), its core premise—that VRIN resources build dynamic capabilities—can be meaningfully extended to labor-intensive textiles with important theoretical adjustments. The key distinction lies in the nature of VRIN resources: in capital-intensive sectors, physical assets (machinery, production lines) and financial capital are the primary sources of inimitability; in labor-intensive textiles, where physical assets are relatively standardized and easily acquired, human capital in the form of digital talent becomes the more critical VRIN resource. This theoretical extension aligns with recent RBV scholarship emphasizing the growing importance of intangible, knowledge-based resources in creating sustainable competitive advantages [9-10]. RBV addresses these by framing DT as a way to leverage limited resources: digital technology assets can optimize existing processes (e.g., using IoT to reduce water waste in dyeing), while, by analyzing equipment data, digital talent can also drive process innovations such as energy-efficient dyeing techniques, in addition to designing recycled fabric lines.

This adjustment aligns with recent RBV extensions that emphasize resource complementarity, whereby digital technology and talent work together to build capabilities. For example, Ma & Tao found that digital talent moderates the effect of digital technology on carbon emission intensity (CEI) in Chinese firms, a finding that informs our focus on heterogeneous DT resources [9]. By applying RBV to textiles, this study responds to empirical evidence that RBV explains green transitions in firms with constrained traditional innovation capacity.

Research Hypothesis

RBV directly guides the hypotheses, which address the study's core research question and fill key gaps in the literature.

First, RBV posits that VRIN resources drive capabilities. For textile firms, DT resources (digital technology assets, digital talent) are VRIN, so they should positively influence GTI, a dynamic capability. This leads to Hypothesis 1:

H1: Digital transformation (measured by digital technology assets as a percentage of total assets and digital talent as a percentage of total employees) has a positive effect on green technological innovation (measured by green process R&D intensity and green product project count) in textile enterprises.

Second, RBV distinguishes between imitable and substitutable resources. Digital talent—human capital with expertise in data analysis and green R&D—is more inimitable than digital technology assets (which can be purchased). Thus, digital talent should have a stronger effect on GTI than technology assets. This leads to Hypothesis 1a (H1a): The positive effect of digital talent on green technological innovation is stronger than the effect of digital technology assets in textile enterprises [11].

Third, RBV links capabilities to outcomes. GTI developed from DT resources is a capability that should improve CEP by reducing emissions and meeting standards. This leads to Hypothesis 2:

H2: Green technological innovation has a positive effect on carbon emission performance (measured by carbon efficiency and carbon footprint compliance rate) in textile enterprises.

Finally, RBV's resource-capability-outcome chain implies that GTI mediates the DT-CEP relationship. DT resources build GTI capabilities, which in turn drive CEP. This directly addresses the study's core research question: Hypothesis 3:

H3: Green technological innovation mediates the relationship between digital transformation and carbon emission performance in textile enterprises, indicating that digital capabilities enhance environmental outcomes primarily through innovation pathways.

These hypotheses extend RBV in three key ways: (1) validating its applicability to labor-intensive textiles, a sector where traditional innovation capacity is limited; (2) disentangling heterogeneous DT resources to explain GTI, addressing the literature's lack of focus on resource type; (3) quantifying the mediation role of GTI, thereby providing empirical evidence for whether the same mechanism observed in capital-intensive sectors holds in textiles. For example, while Deng et al. found that GTI mediates DT-CEP in manufacturing, this study tests whether the same holds in a sector where GTI is constrained by low R&D investment. H1a also addresses the literature's gap in resource heterogeneity, offering insights into whether talent (not just technology) is the key to green innovation in low-innovation firms.

In summary, RBV provides a robust theoretical foundation for this study, linking DT resources to GTI capabilities and CEP outcomes. The framework ensures that every variable, relationship, and hypothesis is grounded in established theoretical logic, while also pushing the boundaries of RBV to address real-world challenges in the textile industry's green transition [12].

Methodology

This study employs a panel data fixed-effects (FE) regression framework to test the hypothesized relationships between DT, GTI, and CEP in textile enterprises. The FE model is appropriate for this research for three reasons. First, it controls for time-invariant unobserved firm heterogeneity (e.g., brand reputation, initial innovation capacity) that could bias estimates of the DT-GTI-CEP relationship, which is critical for RBV's focus on firm-specific resources. Second, it captures dynamic changes over time (e.g., DT investment growth, GTI project cycles), which is essential for analyzing how DT resources build capabilities and improve CEP. Third, it aligns with international methodological standards for longitudinal firm-level data. The design directly supports the study's core objective: testing whether GTI mediates the DT-CEP relationship in a labor-intensive sector where traditional innovation capacity is constrained [13].

RESEARCH DESIGN

Sample Selection

The reasons for the sample selection include: first, A-share listed firms provide publicly available, reliable, and auditable data on digital investment, green innovation, and carbon emissions, which is crucial for conducting rigorous empirical analyses. Second, the panel data period from 2013 to 2022 coincides with the phase of digitalization advancement under China's Made in China 2025 initiative, making listed companies the optimal sample for observing the implementation effects of digital transformation. Selecting listed companies as the research sample to investigate China's textile industry can reflect the carbon emission performance of China's textile sector to a certain extent and still holds important research significance.

The textile industry is widely recognized as a low-innovation sector based on two key indicators: (1) R&D investment is typically limited to 1%–2% of revenue (WTO, 2023), compared to 5%–15% in capital-intensive and high-tech sectors; (2) digital skill penetration is remarkably low, with only 3% of textile employees possessing digital capabilities (China Textile Industry Federation, 2023). In this constrained innovation environment, DT represents a critical and differentiated source of VRIN resources.

The population consists of Chinese A-share listed textile enterprises (2013–2022), chosen for three reasons: (1) China accounts for 50% of global textile output, making its firms representative of the sector's global challenges; (2) A-share data is publicly available, reliable, and widely used in international business research; (3) the 2013–2022 time frame covers the rise of DT in China and aligns with global green transition trends.

We exclude firms with: (1) special treatment (ST) status (financial distress), (2) missing data on key variables (DT, GTI, CEP), and (3) operating in non-textile subsectors (e.g., chemical fibers, which are capital-intensive). The final sample includes 187 firms (1,870 firm-year observations), representing 35% of China's listed textile enterprises [14]. However, we acknowledge potential selection bias, as listed firms are typically larger and better resourced than the majority of SMEs, which comprise over 90% of the global textile sector (WTO, 2023). To mitigate this, we conducted a sensitivity analysis excluding the smallest 25% of firms by assets (results in robustness checks remain consistent).

The sample comprises 187 textile enterprises (1,870 firm-year observations) from three subsectors: textile manufacturing (62%, n = 1,159), apparel (28%, n = 524), and home textiles (10%, n = 187). Geographically, 45% of firms are in Eastern China (high digital infrastructure), 30% in Central China, and 25% in Western China, reflecting China's regional development gradient. Ownership is split between private (75%) and state-owned enterprises (25%), reflecting China's textile sector structure (China Textile Industry Federation, 2023). Table 1 summarizes sample characteristics, confirming representativeness:

Table 1. Sample Characteristics (N=1,870 Firm-Year Observations)

Characteristic	Category	n	%
Subsector	Textile Manufacturing	1,159	62
	Apparel	524	28
	Home Textiles	187	10
Region	Eastern China	842	45
	Central China	561	30
	Western China	467	25

Characteristic	Category	n	%
Ownership	Private	1,402	75
	State-Owned	468	25
	Small (< CNY 500M)	467	25
Firm Size (Assets)	Medium (CNY 500M–1B)	935	50
	Large (> CNY 1B)	468	25

Variable Selection

Variables are operationalized using objective, internationally comparable metrics to align with RBV and avoid common method bias.

Dependent Variable

Following RBV's resource-capability-outcome chain, CEP is measured as two environmental outcomes:

(1) Carbon efficiency (CEP_{Eff}): Output value (CNY 10,000) per ton of CO_2 emissions. Data from the CEADs, a globally recognized source for Chinese carbon data.

(2) Carbon footprint compliance rate ($CEP_{Compliance}$): Binary variable (1 = meets national/local carbon standards; 0 = does not). Data from firm environmental audits, cross-validated with CEADs.

Independent Variable

Following RBV's focus on heterogeneous resources, digital transformation (DT) is measured as two non-substitutable resources:

(1) Digital technology assets ($DT_{Technology}$): Ratio of digital equipment (e.g., IoT sensors, AI-driven production systems) to total assets. Data is from the CSMAR database, a widely used source for Chinese firm-level digital metrics.

(2) Digital talent (DT_{Talent}): Ratio of employees with digital skills (e.g., data scientists, AI engineers) to total employees. Data is manually collected from annual reports, cross-validated with CSMAR's "digital human capital" index.

Mediating Variable

Following RBV's core construct, GTI is operationalized as two dynamic capabilities:

(1) Green process R&D intensity ($GTI_{Process}$): Ratio of green process R&D investment (e.g., energy-efficient dyeing, water recycling) to total revenue. Data from CSMAR's Green Innovation database.

(2) Green product project count ($GTI_{Product}$): Number of new green product projects (e.g., recycled textiles, low-carbon fabrics) in a year. Data from firm environmental reports, validated with third-party sustainability ratings (S&P Global, 2023).

Control Variables

To isolate the DT-GTI-CEP relationship, we control for:

(1) Firm size: Natural log of total assets.

(2) Financial leverage: Debt-to-equity ratio.

(3) Ownership: Dummy variable (1 = state-owned enterprise; 0 = private).

(4) Regional GDP per capita: Natural log of regional GDP per capita, and the data were obtained from the 2023 National Bureau of Statistics.

(5) Regional environmental regulation (Env_{Reg}): The Env_{Reg} index is constructed as the ratio of provincial environmental penalty cases to total industrial firms, capturing top-down regulatory pressure and the intensity of provincial/municipal environmental policy enforcement.

Data Source

(1) DT and financial data: CSMAR database (internationally recognized for Chinese firm-level data).

(2) GTI data: CSMAR Green Innovation Index and manual coding of annual/environmental reports.

(3) CEP data: CEADs (carbon emissions) and firm environmental audits (compliance).

(4) Control variables: National Bureau of Statistics (regional GDP), CSMAR (ownership, firm size, financial leverage, Env_{Reg}).

Data Cleaning: (1) Outliers: We winsorize continuous variables at the 1% level to reduce the impact of extreme values (e.g., firms with unusually high DT investment). (2) Missing Data: We use multiple imputation with chained equations (MICE) to impute missing values (5% of observations), a method validated for panel data. (3) Consistency Checks: We cross-validate data from multiple sources (e.g., DT_{Talent} from annual reports vs. CSMAR) to ensure accuracy [15].

Model Construction

To empirically test the proposed hypotheses, we construct a set of panel FE regression models. These models are designed to analyze the pathway from DT to GTI and then to CEP, and to test for the potential mediating effect of GTI. In order to mitigate reverse causality, whereby enterprises with superior CEP might proactively invest more in digital transformation, we use lagged DT variables in all relevant equations, which is consistent with prior panel data research. The specific econometric models are as follows:

Model 1: The effect of digital transformation on green technology innovation (Testing Hypothesis 1)

$$GTI_{it} = \alpha_1 + \beta_1 DT\_Tech_{i,t-1} + \beta_2 DT\_Talent_{i,t-1} + \gamma_1 X_{it} + \mu_i + \varepsilon_{1,it} \tag{1}$$

Model 2: The effect of green technology innovation on carbon emission performance (Testing Hypothesis 2)

$$CEP_{it} = \alpha_2 + \beta_3 GTI_{it} + \gamma_2 X_{it} + \mu_i + \varepsilon_{2,it} \tag{2}$$

Model 3: The direct effect of digital transformation on carbon emission performance (Total Effect, for Mediation Analysis)

$$CEP_{it} = \alpha_3 + \beta_4 DT\_Tech_{i,t-1} + \beta_5 DT\_Talent_{i,t-1} + \gamma_3 X_{it} + \mu_i + \varepsilon_{3,it} \tag{3}$$

Model 4: The effect of digital transformation and green technology innovation on carbon emission performance (Testing Mediation, Hypothesis 3)

$$CEP_{it} = \alpha_4 + \beta_6 DT\_Tech_{i,t-1} + \beta_7 DT\_Talent_{i,t-1} + \beta_8 GTI_{it} + \gamma_4 X_{it} + \mu_i + \varepsilon_{4,it} \tag{4}$$

Where:

(1) GTI_{it} is the green technology innovation of firm i in year t, measured either as process innovation ($GTI_{Process}$) or product innovation ($GTI_{Product}$).

(2) $DT\_Tech_{i,t-1}$ and $DT\_Talent_{i,t-1}$ indicate the lagged values (by one period) of digital technology resources and digital talent resources, respectively, for firm i.

(3) CEP_{it} is the carbon emission performance of firm i in year t.

(4) X_{it} is a vector of control variables (firm size, financial leverage, ownership, regional GDP per capita, Env_{Reg}, etc).

(5)μ_i represents the firm-specific fixed effects to control for unobserved, time-invariant heterogeneity.

(6) $\varepsilon_{k,it}$ (*k = 1, 2, 3, 4*) are the idiosyncratic error terms in each model.

EMPIRICAL RESULTS AND ANALYSIS

We use Stata 17 for all analyses, with code shared on GitHub to support reproducibility. The analysis follows three steps, aligned with international methodological standards [6,7].

Descriptive Statistics and Analysis

Table 2 reports descriptive statistics for core variables, with cross-subsector differences tested via one-way ANOVA. Key patterns emerge from Table 2:

(1) DT and GTI: Textile manufacturing firms (62% of sample) invest more in digital technology ($DT_{Technology}$ = 9%) and talent (DT_{Talent} = 5%) than apparel (7%, 3%) or home textiles (6%, 2%). This aligns with their higher GTI activity ($GTI_{Process}$ = 4%, $GTI_{Product}$ = 2.56 projects).

(2) CEP: Textile manufacturing firms also show better carbon performance (CEP_{Eff} = 13.1%, $CEP_{Compliance}$ = 72%), consistent with the hypothesis that DT and GTI drive emission reductions [16].

(3) Cross-Subsector Differences: All variables show statistically significant differences ($p < 0.01$), confirming that subsector-specific factors (e.g., production complexity) influence DT, GTI, and CEP.

Table 2. Descriptive Statistics and Cross-Subsector Differences (N = 1,870)

Variable	Mean	SD	Textile Manufacturing	Apparel	Home Textiles	F-Value	p
Digital Technology Assets ($DT_{Technology}$)	0.08	0.05	0.09	0.07	0.06	11.23	<0.001
Digital Talent (DT_{Talent})	0.04	0.03	0.05	0.03	0.02	15.67	<0.001

Green Process R&D ($GTI_{Process}$)	0.03	0.02	0.04		0.02	0.01		22.45	<0.001
Green Product Projects ($GTI_{Product}$)	2.15	1.23	2.56		1.89	1.45		18.78	<0.001
Carbon Efficiency (CEP_{Eff})	12.34	4.56	13.12		11.56	10.23		9.87	<0.01
Carbon Compliance ($CEP_{Compliance}$)	0.65	0.48	0.72		0.61	0.53		8.91	<0.01

Analysis of Regression Results

We test hypotheses using FE regression (for H1, H2) and bootstrapped mediation analysis (for H3). Results are organized by hypothesis below.

Hypothesis 1: DT Resources Positively Influence GTI

Hypothesis 1 posits that digital technology assets ($DT_{Technology}$) and digital talent (DT_{Talent}), as VRIN resources, enhance GTI. Table 3 reports FE regression results:

Table 3. Fixed-Effects Regression Results for Hypothesis 1 (DT → GTI)

Dependent Variable	Predictor	β	SE	p	95% CI	R^2
$GTI_{Process}$	$DT_{Technology}$	0.12	0.04	<0.001	[0.04, 0.20]	0.23
	DT_{Talent}	0.21	0.05	<0.001	[0.11, 0.31]	
	Firm Size	0.08	0.04	<0.05	[0.01, 0.15]	
$GTI_{Product}$	$DT_{Technology}$	0.09	0.03	<0.01	[0.03, 0.15]	0.19
	DT_{Talent}	0.18	0.04	<0.001	[0.10, 0.26]	
	Firm Size	0.07	0.03	<0.05	[0.01, 0.13]	

Results support Hypothesis 1: both DT resources significantly predict GTI. For green process R&D ($GTI_{Process}$), $DT_{Technology}$ ($\beta = 0.12$, SE = 0.04, $p < 0.001$) and DT_{Talent} ($\beta = 0.21$, SE = 0.05, $p < 0.001$) both predict GTI. For $GTI_{Product}$, $DT_{Technology}$ ($\beta = 0.09$, SE = 0.03, $p < 0.01$) and DT_{Talent} ($\beta = 0.18$, SE = 0.04, $p < 0.001$) both predict GTI. Hypothesis 1a: DT_{Talent} has a stronger effect on GTI than $DT_{Technology}$. We compare coefficients using a z-test. For $GTI_{Process}$, DT_{Talent}'s effect is significantly larger than $DT_{Technology}$ ($\Delta\beta = 0.09$, $z = 1.98$, $p < 0.05$). For $GTI_{Product}$, the difference is also significant ($\Delta\beta = 0.12$, $z = 2.03$, $p < 0.05$). These results confirm H1a: DT_{Talent}, which is an inimitable human resource, is more impactful for green innovation in textiles than purchasable technology assets.

Hypothesis 2: GTI Positively Influences CEP

Hypothesis 2 links GTI (a dynamic capability) to CEP. Table 4 reports FE regression results:

Table 4. Fixed-Effects Regression Results for Hypothesis 2 (GTI → CEP)

Dependent Variable	Predictor	β	SE	p	95% CI	R^2
CEP_{Eff}	$GTI_{Process}$	0.15	0.05	<0.01	[0.05, 0.25]	0.18
	$GTI_{Product}$	0.11	0.03	<0.05	[0.02, 0.20]	
	Firm Size	0.10	0.04	<0.05	[0.02, 0.18]	
$CEP_{Compliance}$	$GTI_{Process}$	0.22	0.07	<0.01	[0.08, 0.36]	0.15
	$GTI_{Product}$	0.20	0.06	<0.05	[0.03, 0.37]	
	Firm Size	0.15	0.06	<0.05	[0.02, 0.24]	

Table 4 confirms Hypothesis 2: GTI significantly improves CEP.

(1) For CEP_{Eff}: Green process R&D ($GTI_{Process}$) has a medium effect ($\beta = 0.15$, $p < 0.01$); green product projects ($GTI_{Product}$) show a smaller but significant effect ($\beta = 0.11$, $p < 0.05$).

(2) For $CEP_{Compliance}$: $GTI_{Process}$ has a stronger effect ($\beta = 0.22$, $p < 0.01$), while $GTI_{Product}$ ($\beta = 0.20$, $p < 0.05$) is marginally significant. These results align with the capability-outcome logic of RBV: process innovation (e.g.,

energy-efficient dyeing) tends to produce more immediate emission reductions, while product innovation (e.g., recycled textiles) has a slower, smaller impact on compliance [17].

Hypothesis 3: GTI Mediates the DT-CEP Relationship

The core research question examines whether GTI mediates the relationship between DT and CEP, and to what extent. To test this, we employ the bootstrapping method (5,000 iterations) using Stata's mediate command, which does not rely on normal distribution assumptions and yields robust confidence intervals for indirect effects. Table 5 presents the bootstrapped mediation results for Hypothesis 3.

Table 5. Bootstrapped Mediation Results for Hypothesis 3 (N = 5,000 Bootstrap Iterations)

DT Resource	Mediator	Dependent Variable	Effect Type	Coefficient (β)	95% Confidence Interval	Significance
$DT_{Technology}$	$GTI_{Process}$	CEP_{Eff}	Indirect Effect	0.018	[0.006, 0.031]	Yes
	$GTI_{Product}$	CEP_{Eff}	Indirect Effect	0.010	[0.002, 0.018]	Yes
$DT_{Technology}$	$GTI_{Process}$	$CEP_{Compliance}$	Indirect Effect	0.026	[0.009, 0.033]	Yes
DT_{Talent}	$GTI_{Process}$	CEP_{Eff}	Indirect Effect	0.032	[0.010, 0.053]	Yes
	$GTI_{Product}$	CEP_{Eff}	Indirect Effect	0.020	[0.004, 0.036]	Yes
DT_{Talent}	$GTI_{Process}$	$CEP_{Compliance}$	Indirect Effect	0.039	[0.015, 0.055]	Yes
	$GTI_{Product}$	$CEP_{Compliance}$	Indirect Effect	0.013	[0.003, 0.038]	Yes

All 95% confidence intervals exclude zero, confirming that GTI significantly mediates the DT_{CEP} relationship, thus supporting Hypothesis 3.

Both $DT_{Technology}$ and DT_{Talent} positively and significantly affect CEP, and their effects are partially mediated by GTI. After incorporating the environmental regulation (Env_{Reg}) variable, the direct effect of DT decreased by approximately 10%, while the mediating effect of GTI remained statistically significant (with the mediating effect interval shifting to 7.9%–16.5%). This result indicates that although environmental regulation policies have generally improved corporate CEP, the innovation-mediated impact of DT remains significant, and the effect of digital transformation transmitted through innovation still holds statistical significance. The supplementary analysis above enhances the causal inference validity of this study and makes the research conclusions more aligned with the policy-driven development context of emerging economies. To further validate these findings, we decomposed the mediation path into direct and indirect effects (see Table 6).

Table 6. Results of the Mediation Effect Decomposition

Path	Effect Type	Coefficient	95% Confidence Interval	Significance
$DT_{Technology} \rightarrow$ CEP	Direct effect	0.100	[0.020, 0.180]	Yes
$DT_{Talent} \rightarrow$ CEP	Direct effect	0.120	[0.030, 0.210]	Yes
$DT_{Technology} \rightarrow$ GTI $\rightarrow$ CEP	Indirect effect	0.030	[0.012, 0.048]	Yes
$DT_{Talent} \rightarrow$ GTI $\rightarrow$ CEP	Indirect effect	0.045	[0.020, 0.070]	Yes

Both types of DT resources exert significant direct and indirect effects on CEP. The indirect effect of digital technology on CEP through GTI is 0.030 (95% CI [0.012, 0.048]). The indirect effect of DT_{Talent} on CEP through GTI is 0.045 (95% CI [0.020, 0.070]).

These results indicate that GTI plays a significant partial mediation role: digital transformation enhances carbon performance both directly and indirectly through green innovation. Moreover, DT_{Talent} shows a stronger mediating influence than technology assets, consistent with the RBV logic that human capital, being inimitable and non-substitutable, drives dynamic innovation capabilities more effectively [18]. This supports the view that human capital is critical for leveraging digital technologies effectively. Specifically, digital talent bridges the gap between software capabilities and physical engineering. For example, in energy-efficient dyeing processes, data analysts and engineers use machine learning to analyze sensor data from dye vats, optimizing temperature curves and chemical dosages to reduce water and energy consumption. This capability to translate data insights into tangible process improvements explains why digital talent drives innovation more effectively than static hardware assets.

In summary, the empirical results strongly confirm Hypothesis 3, demonstrating that textile enterprises can enhance carbon emission performance by developing green technological innovation through digital transformation—particularly by cultivating DT_{Talent} and integrating it with green R&D. These findings robustly confirm Hypothesis 3, indicating that green technological innovation partially mediates the relationship between digital transformation and carbon emission performance. Subsequent robustness checks further validate this mediating pathway.

Robustness Checks

To confirm result stability, we conducted three robustness tests:

Alternative Dependent Variable: Carbon Intensity (Reverse of CEP_{Eff})

We replaced carbon efficiency (CEP_{Eff} = output/CO_2) with carbon intensity (CEI = CO_2/output), a widely used inverse metric. The results remain consistent with the main findings:

(1) $DT_{Technology}$ ($\beta = –0.10$, $p < 0.01$) and DT_{Talent} ($\beta = –0.18$, $p < 0.001$) significantly reduce CEI.

(2) $GTI_{Process}$ ($\beta = –0.12$, $p < 0.05$) and $GTI_{Product}$ ($\beta = –0.09$, $p < 0.05$) also reduce CEI, confirming that DT and GTI improve CEP via lower emissions.

Instrumental Variable (IV) Analysis for $DT_{Technology}$

To address reverse causality—the possibility that firms with better CEP may invest more in digital technology—we used regional broadband penetration (per 100 people) as an IV for $DT_{Technology}$ [19]. Broadband penetration is exogenous because firms cannot control regional infrastructure. Results replicate the main findings:

(1) IV estimate for $DT_{Technology} \rightarrow GTI_{Process}$: $\beta = 0.15$, $p < 0.05$.

(2) IV estimate for $DT_{Technology} \rightarrow CEP_{Eff}$: $\beta = 0.12$, $p < 0.05$.

Subsample Analysis: Textile Manufacturing Firms Only

Textile manufacturing firms represent 62% of the sample and invest most in DT/GTI. Repeating analyses for this subsample confirms the main results:

(1) $DT_{Talent} \rightarrow GTI_{Process}$: $\beta = 0.32$, $p < 0.001$ (vs. 0.21 in full sample).

(2) $GTI_{Process} \rightarrow CEP_{Compliance}$: $\beta = 0.38$, $p < 0.001$ (vs. 0.22 in full sample).

These tests confirm that results are not driven by subsector heterogeneity. Additionally, to address size-related selection bias, we performed a subsample analysis excluding the smallest 25% of firms by total assets (n = 1,402 observations). The mediation effect of GTI remains significant (7.9%–16.5%), though slightly attenuated, suggesting robustness.

CONCLUSIONS AND DISCUSSION

In summary, this study bridges theoretical and empirical gaps by demonstrating that digital transformation can effectively promote sustainable performance through innovation-driven mechanisms, even in low-innovation, labor-intensive industries such as textiles.

Main Findings

(1) Drawing on panel data from 187 Chinese A-share listed textile enterprises (2013–2022), we empirically examined the DT-GTI-CEP mechanism. Results from fixed-effects regressions and bootstrapped mediation tests support all hypotheses.

(2) Digital transformation significantly enhances GTI, confirming Hypothesis 1. Both $DT_{Technology}$ and DT_{Talent} promote green innovation, but talent has a stronger effect. These results are consistent with the RBV perspective that inimitable human capital (DT_{Talent}) serves as a stronger driver of dynamic innovation capabilities than replicable physical assets.

(3) GTI significantly improves CEP, validating Hypothesis 2. Green process R&D has a greater impact than green product projects, indicating that operational process improvements yield immediate emission reductions.

(4) GTI mediates the DT-CEP relationship, supporting Hypothesis 3. The mediation proportion ranges from 7.9% to 16.5%, providing new empirical evidence that DT drives CEP both directly and indirectly through innovation capabilities [20].

These findings indicate that DT’s environmental benefits stem not only from operational efficiency but also from fostering innovation-driven carbon reduction.

Theoretical Contributions

This research makes three contributions to international scholarship:

(1) Extending RBV applicability to labor-intensive sectors. Prior RBV-based studies focused on capital-intensive manufacturing. By demonstrating that heterogeneous digital resources (digital technology assets and digital talent) drive environmental performance in the textile sector, this study confirms RBV's relevance in low-innovation contexts.

(2) Disentangling heterogeneous DT resources. By separating $DT_{Technology}$ and DT_{Talent}, this study refines RBV's resource categorization. The finding that talent exerts a stronger impact than technology supports the argument that inimitable human capital is central to sustaining dynamic innovation capabilities.

(3) Quantifying GTI's mediating role. The analysis empirically measures GTI's mediation strength (8%–18%), providing a benchmark for future sectoral comparisons. It demonstrates that even in labor-intensive industries, digitalization contributes to decarbonization via innovation pathways.

Methodologically, we employ panel fixed-effects regression combined with bootstrapped mediation to enhance the robustness of our results. This approach addresses unobserved heterogeneity and ensures international comparability.

Practical Implications

The findings offer actionable insights for firms, policymakers, and international organizations:

(1) For Firms

Prioritize DT_{Talent} cultivation over hardware acquisition. Upskilling employees in data analytics and sustainability design yields more substantial gains in GTI and CEP than investing solely in digital infrastructure.

(2) For Policymakers

Policymakers should design targeted incentives to promote DT_{Talent} development and green process R&D in the textile sector. Specific programs, such as tax credits or training subsidies, can help small and medium-sized enterprises leverage DT for carbon reduction.

(3) For International Organizations

Aligning textile digitalization efforts with key SDGs is essential. The establishment of cross-country alliances, such as a Digital Green Textile Alliance, can facilitate knowledge sharing, workforce upskilling, and adoption of green innovations, especially in developing economies such as India and Bangladesh.

Limitations and Future Research

Despite its contributions, this study has three limitations.

(1) Sample Scope. This study focuses on 187 textile enterprises listed on China's A-share market. The findings of this paper are primarily applicable to listed firms. Listed companies are larger and tend to have more advanced governance and greater access to technological and human resources than most textile SMEs. Therefore, the results of this paper should be regarded as an upper-bound benchmark rather than a representative depiction of China's entire textile industry. It is recommended that future studies expand the sample scope. Specifically, future research should strive to incorporate data from SMEs and non-listed enterprises, as well as comparative data from other major textile-producing countries.

(2) Measurement Precision. GTI indicators rely on R&D intensity and project counts; incorporating patent-based or process-efficiency data would yield more nuanced insights.

(3) Temporal Coverage. The dataset ends in 2022, capturing early DT development stages. Extending the analysis to include post-2023 technologies (e.g., generative AI, digital twins) could reveal new mechanisms.

Future research should explore cross-national comparisons and multi-mediator frameworks (e.g., supply chain optimization). It should also examine the longitudinal effects of digital capability accumulation on sustainability outcomes.

Author Contributions

Conceptualization – Ma T; data curation – Ma T; methodology – Ma T; writing-original draft – Ma T; writing-review & editing – Ma T. The author has read and agreed to the published version of the manuscript.

Conflicts of Interest

The author declares no conflict of interest.

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REFERENCES

[1] Deng FM, Cai L, Ma XL. Does digital transformation restrict the carbon emission intensity of enterprises? Evidence from listed manufacturing enterprises in China. Nat. Resour. Forum. 2024; 48(2):364–384. doi: 10.1111/1477-8947.12381

[2] Yang P, Guo K, Jia J, Yin Y. Corporate digital transformation and carbon emission intensity: Empirical evidence from listed companies in China. PLOS ONE. 2024; 19(12):e0313870. doi: 10.1371/journal.pone.0313870

[3] Hou J, Bai WT, Sha DC. Does the digital economy successfully facilitate carbon emission reduction in China? Green technology innovation perspective. Science, Technology and Society. 2023; 28(4): 535-560. doi: 10.1177/09717218231161235

[4] Qu F, She W. Artificial Intelligence Technology and Regional Carbon Emission Performance: Does Energy Transition or Industrial Transformation Matter?. Sustainability. 2025; 17(5):1844. doi: 10.3390/su17051844

[5] Zhao SL, Deng H, Cao JK, Gustaf M. Digital transformation of construction enterprises and carbon emission reduction: Evidence from listed companies. Front. Environ. Sci. 2025; 13:1570182. doi: 10.3389/fenvs.2025.1570182

[6] Baron RM, Kenny DA. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 1986; 51(6):1173-1182. doi: 10.1037/0022-3514.51.6.1173

[7] Hayes AF. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. New York, NY, USA: Guilford Publications. 2017. Available from: www.guilford.com/p/hayes3

[8] Barney J. Firm resources and sustained competitive advantage. J. Manag. 1991; 17(1):99-120. doi: 10.1177/014920639101700108

[9] Ma Y, Tao P. A Perspective on Management Myopia: The Impact of Digital Transformation on Carbon Emission Intensity. Sustainability. 2023; 15(12):9417. https://doi.org/10.3390/su15129417

[10] Ding R and Wang H. Digital Transformation of Enterprises and Carbon Emission Reduction—Based on the Moderating Effect Test of Government Subsidies. Acad. J. Bus. Manag. 2024; 6(8):12-20. doi: 10.25236/AJBM.2024.060802

[11] Guan Y, Yang J, Wang R, Zhang L, Wang M. Exploring the Role of Energy Consumption Structure and Digital Transformation in Urban Logistics Carbon Emission Efficiency. Atmosphere. 2025; 16(8):929. doi: 10.3390/atmos16080929

[12] Tang D. Research on the Influencing Mechanism of Digital Transformation on the Synergistic Effect and Carbon Emission Performance of Enterprise Green Supply Chain. Res. Econ. Manag. 2024; 5(4):1-13. doi: 10.22158/rem.v9n1p100

[13] Xu J. Can Green Digital Synergy Improve the Carbon Emission Performance in the Central and Western Regions?. Adv. Econ. Manag. Res. 2024; 9:2789. doi: 10.56028/aemr.12.1.510.2024

[14] Wang Y, Zhang X, Lin F, Peng M. The role of digital governance on carbon emission performance: Evidence from the cities in Yangtze River Delta, China, Environ. Res. Commun. 2023; 5(8):085003. doi: 10.1088/2515-7620/acf2dc

[15] He Y, Wang H. The impact of carbon emission reduction policies on corporate ESG performance: Evidence from low-carbon city pilots. Applied Economics. 2025; 1-18. doi: 10.1080/00036846.2025.2484027

[16] Ma J, Chen HC, Wang K, Ma YF. Research on the Impact of Digital Transformation on Carbon Performance of Chinese Manufacturing Enterprises. SAGE Open. 2025; 15(2):1-17. doi: 10.1177/21582440251323957

[17] Li S, Ao X, Zhang M, Pu M. ESG performance and carbon emission intensity: Examining the role of climate policy uncertainty and the digital economy in China's dual-carbon era. Front. Environ. Sci. 2025; 12:1526681. doi: 10.3389/fenvs.2024.1526681

[18] Deng J, Lin W, Huang J, Cai Y, Wang W. Research on the impact of the ESG rating divergence of manufacturing firms on carbon emission intensity. PLOS ONE. 2025; 20(6):e0323929. doi: 10.1371/journal.pone.0323929

[19] Li J, Xie Z, Fu Y. The path of corporate low-carbon behavioral change: The impact of digital transformation on corporate green sports brand loyalty. Journal of Environmental Management. 2025; 374(000):124057. doi: 10.1016/j.jenvman.2025.124057

[20] Tian B, Song R, Qu H, Li H. Sustainable Development in the Textile and Apparel Industry: ESG Performance, Digital Transformation, and Corporate Value. Textile Leather Rev. 2025; 8:349-376. doi: 10.31881/TLR.2025.007