

Article

Digital–Green Collaborative Technological Innovation and Firm Transformation: A Systems Perspective on Total Factor Productivity

Bingtao Qin ¹, Xiaoqian Yang ¹, Yongwei Yu ^{2,3,*} , Junhua Guo ^{2,*} and Huaiyu Zheng ⁴¹ Business School, University of Shanghai for Science and Technology, Shanghai 200093, China² School of International and Public Affairs, Shanghai Jiao Tong University, Shanghai 200030, China³ China Institute for Urban Governance, Shanghai Jiao Tong University, Shanghai 200030, China⁴ Northeast Asian College, Jilin University, Changchun 130012, China

* Correspondence: yuyongwei@sjtu.edu.cn (Y.Y.); guojunhuasjtu@126.com (J.G.)

Abstract

Digital and green technological innovations are increasingly viewed as interdependent components of firm transformation, yet their combined effects are still insufficiently understood from a systems perspective. Rather than treating digitalization and greening as separate innovation trajectories, this study conceptualizes their integration as digital–green collaborative technological innovation and examines whether this socio-technical synergy improves firm-level total factor productivity (TFP). Using panel data for Chinese A-share listed companies from 2008 to 2022, we construct firm-level measures of digital innovation, green innovation, and their interaction based on patent information, and employ multi-dimensional fixed-effects models to assess their productivity effects. The results show that digital–green collaborative technological innovation significantly improves corporate TFP, and this finding remains robust after addressing potential endogeneity, replacing the TFP measure, excluding information-technology-intensive industries, expanding the sample period, and employing invention patents as an alternative proxy for innovation quality. Heterogeneity analysis indicates that the productivity-enhancing effect is more pronounced among non-state-owned enterprises, firms located in central China, and firms operating in regions with stronger intellectual property protection. Further decomposition of TFP reveals that digital–green synergy promotes firm transformation through three channels: improving micro-level production efficiency, optimizing labor allocation efficiency, and enhancing capital allocation efficiency. These findings contribute to systems-oriented research on technological innovation by showing how complementary digital and green capabilities jointly reshape production systems and factor allocation. They also provide practical implications for firms and policymakers seeking to promote sustainable transformation through integrated innovation strategies.

Keywords: digital–green collaborative technological innovation; systems perspective; firm transformation; total factor productivity; factor allocation efficiency

JEL Classification: D22; H32; O30; Q55



Academic Editor: Andrea Pitasi

Received: 16 May 2026

Revised: 24 June 2026

Accepted: 6 July 2026

Published: 9 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The global transition toward sustainable and digitally enabled development is reshaping the organization of production, innovation, and resource allocation within firms. Digital technologies, such as artificial intelligence, cloud computing, big data analytics, and the Internet of Things, are changing how firms collect information, coordinate activities,

and optimize decision-making. At the same time, green technological innovation has become essential for reducing resource consumption, lowering emissions, and supporting long-term environmental sustainability. These two innovation trajectories are increasingly intertwined: digital technologies can improve the efficiency and scalability of green innovation, while green transformation creates new application scenarios and strategic demands for digital technologies.

From a systems perspective, digitalization and greening should not be understood as two isolated technological processes. In this study, the systems perspective refers to an analytical view of firms as embedded socio-technical systems in which technological capabilities, organizational routines, factor allocation, market institutions, and policy environments interact through feedback and complementarity. Digital–green collaborative technological innovation is therefore defined not as the mere coexistence of digital patents and green patents, but as the coordinated combination of digital knowledge, environmental knowledge, and organizational reconfiguration that jointly reshapes production and resource-allocation processes. This perspective extends beyond estimating statistical relationships among variables because it clarifies the system components, their interactions, and the channels through which technological complementarity can influence firm transformation. For example, digital monitoring and data analytics can support cleaner production, energy management, and supply-chain coordination, while green innovation can redirect digital applications toward sustainability-oriented value creation. However, such collaboration may also involve coordination costs, organizational adjustment, and resource reconfiguration, making its net effect on firm performance an empirical question.

Total factor productivity (TFP) provides an appropriate lens through which to evaluate this transformation. As a comprehensive indicator of economic efficiency and growth quality [1], TFP reflects not only technological progress but also the effectiveness with which labor, capital, and other resources are allocated. For firms, improving TFP is central to moving from input-driven expansion toward innovation-driven, high-quality development [2]. Since enterprises are the primary agents of technological innovation and the fundamental units of production [3], examining how digital–green collaborative innovation affects firm-level TFP can help clarify the micro-foundations of sustainable economic transformation.

Existing studies have made important progress in examining the economic effects of digital innovation and green innovation, but most of them analyze these two dimensions separately. Research on digital innovation emphasizes recombination, platform-based knowledge flows, and data-enabled organizational change, whereas studies of green innovation focus more on environmental regulation, resource efficiency, and sustainability-oriented technological upgrading. The systems and sustainability-transitions literature further suggests that technological change is shaped by interactions among actors, institutions, infrastructures, and market selection environments. However, these streams have not been sufficiently connected at the micro-enterprise level. As a result, the systemic complementarity between digital and green technologies remains underexplored. Several questions remain open: How can the synergy between digital and green innovation be measured at the firm level? Does this complementarity improve TFP beyond the separate effects of digital and green innovation? Through which channels does it operate? In particular, it remains unclear whether digital–green collaborative innovation improves TFP mainly by enhancing internal production efficiency or by optimizing the allocation of labor and capital factors.

To address these questions, this study uses panel data on Chinese A-share listed companies from 2008 to 2022 and constructs a firm-level indicator of digital–green collaborative technological innovation based on the interaction between digital and green patent activities. We then employ multi-dimensional fixed-effects models to examine the impact of this

synergy on corporate TFP. Furthermore, we decompose TFP into micro-level production efficiency, labor allocation efficiency, and capital allocation efficiency, thereby opening the black box of the productivity effects of digital–green collaborative innovation.

This study makes three main contributions. First, it develops a systems-oriented framework that integrates digital and green innovation into a unified analytical perspective, while explicitly distinguishing technological collaboration from the simple coexistence of two innovation activities. Second, it provides firm-level empirical evidence on the productivity effect of digital–green collaborative technological innovation and tests the robustness of this effect through multiple strategies. Third, by decomposing TFP, it identifies the internal production and factor allocation channels through which technological complementarity supports firm transformation. Rather than claiming to conclusively prove all dimensions of synergistic value creation, this study offers evidence that the interaction between digital and green innovation is positively associated with TFP and helps connect micro-level corporate innovation behavior with broader debates on sustainable and digitally enabled transformation.

2. Literature Review

2.1. Digital Technology Innovation and High-Quality Development of Enterprises

Digital technological innovation serves as the bedrock of the digital economy and the primary driver of corporate digital maturity [4]. It is widely defined as the creation of novel products, services, or business models leveraged by information, computing, communication, and connectivity technologies [5]. The pervasive adoption of automation and Artificial Intelligence (AI) has fundamentally restructured corporate production by substituting traditional labor, optimizing factor inputs, and reconfiguring value chains [6]. Empirical evidence suggests that digitalization significantly bolsters corporate innovation [7] and enhances TFP by streamlining management, reducing internal frictions, and accelerating innovation responsiveness [8]. Furthermore, the positive externalities of digital knowledge and supply-demand matching via digital platforms are recognized as vital conduits for value creation [9,10]. Collectively, the literature affirms the transformative power of digital technology in shifting enterprises from “factor-driven” to “data-empowered” growth [11].

2.2. Green Technology Innovation and High-Quality Development of Enterprises

Green innovation is the linchpin for low-carbon transitions. Current research predominantly focuses on policy-driven incentives, suggesting that mechanisms such as carbon emissions trading [12], environmental tax reforms, and green finance can effectively stimulate energy efficiency and green patenting [13,14]. Beyond regulatory compliance, green innovation enhances both environmental-social performance and long-term financial viability [15]. Moreover, pressure from external stakeholders—including the media, public, and investors—acts as a potent catalyst for sustainable technological adoption [16].

2.3. Synergistic Effects of Digital–Green Technological Innovation

Recently, scholars have begun exploring the intersection of digital and green domains. For instance, the Pressure-State-Response (PSR) framework has been utilized to articulate how this synergy drives manufacturing sustainability [17]. Resource Orchestration Theory has been applied to illustrate how digital capabilities empower green transitions through dynamic resource reconfiguration [18], while the potential of synergistic growth through R&D-led technology integration has been argued for [19]. International research on sustainability transitions, digital innovation, and environmental competitiveness also highlights that productivity gains depend on how firms combine technological search, institutional support, and complementary assets rather than on a single technological input alone [20–24].

Despite these advancements, the existing literature still has several limitations. First, many studies remain descriptive or focus on either digital transformation or green innovation in isolation, leaving the complementarity between the two insufficiently theorized. Second, existing empirical work often relies on macro-level indicators or aggregate indices, whereas firm-level quantitative evidence on digital–green collaboration remains limited. Third, the specific pathways, particularly the heterogeneous effects on production efficiency versus factor allocation efficiency, remain a “black box.” Finally, although the Chinese context provides a valuable setting for observing large-scale digital and green transitions, more engagement with international systems and transition studies is needed to position the findings within broader academic debates.

Positioned within this scholarly landscape, this paper seeks to make several more precise contributions. Conceptually, it treats digital–green collaborative technological innovation as a complementary relationship between digital and environmental knowledge bases rather than as a broad claim that all digital and green activities automatically create synergy. Empirically, it develops an interactive quantitative indicator to test whether this complementarity is associated with higher TFP and further unpacks the underlying micro-mechanisms by decomposing TFP gains into production efficiency, labor allocation efficiency, and capital allocation efficiency. In terms of broader significance, it contextualizes enterprise-level technological complementarity within systems-oriented debates on sustainable transformation, thereby providing micro-founded evidence for urban and industrial low-carbon transition strategies. Methodologically, it uses interaction terms as an empirical approximation of complementarity; this design can identify whether the joint presence of digital and green innovation is associated with additional productivity effects, but it should not be interpreted as definitive proof of all forms of synergistic value creation.

3. Theoretical Analysis

3.1. Digital Technology Innovation and Green Technology Innovation Synergy and High-Quality Development of Enterprises

Digital technology innovation and green technology innovation are not only the core drivers of contemporary global development but also constitute the strategic cornerstone of a firm’s “Sustainability Transitions.” The synergistic development of this “twin transition”—digitalization and greening—aligns with national digital strategies and carbon neutrality goals. From a contemporary perspective, the replicability and real-time nature of digital technology provide efficient foundational support for green technology, while green technology offers a sustainable value orientation for digital applications.

According to Schumpeter’s endogenous growth theory, technological innovation is a revolutionary force for economic growth. Synergistic innovation operates through the mechanism of “creative destruction” [25], phasing out traditional production paradigms characterized by high energy consumption and low efficiency. From a systems perspective, this process involves at least four interacting components: digital technological capabilities, green technological capabilities, organizational routines that integrate the two, and external institutional environments that shape incentives and constraints. The digital–green collaboration may enhance resource recycling rates and reduce energy intensity, thereby helping firms internalize environmental externalities into competitive advantages. Nevertheless, the empirical specification in this paper captures complementarity through an interaction term. It can indicate that digital and green innovations reinforce each other in relation to TFP, but it does not by itself prove a literal “ $1 + 1 > 2$ ” value-creation process in every firm.

It is noteworthy that synergistic innovation is not frictionless. Firms face significant “coordination costs” and organizational restructuring costs when integrating cross-domain knowledge, such as Information and Communication Technology and environmental

engineering [26]. Furthermore, large-scale investment in digital infrastructure in the short term may trigger a “resource crowding-out effect,” increasing R&D uncertainty. The enhancement of TFP only manifests when the efficiency gains brought by synergy outweigh these potential trade-offs.

The distinction between simultaneous innovation and genuine collaboration is therefore central to this paper. A firm may conduct digital innovation and green innovation in the same period without integrating them. Digital–green collaborative technological innovation exists when digital technologies are used to sense, monitor, simulate, coordinate, or scale green innovation activities, or when green objectives reshape the direction and application scenarios of digital innovation. In the empirical design, this collaboration is approximated by the interaction between digital patenting and green patenting. This measure is conservative: it captures observable technological overlap and complementarity, while acknowledging that deeper organizational synergy may require additional qualitative evidence.

Based on the above analysis, this paper proposes the core hypothesis:

H1: *Digital–green collaborative technological innovation enhances the TFP of enterprises.*

3.2. *The Mechanism of Synergy Between Digital Technology Innovation and Green Technology Innovation in Promoting High-Quality Development of Enterprises*

Differences in economic development levels among countries are largely due to differences in overall TFP [27]. Misallocation of resources may reduce overall total factor productivity. Improvements in overall TFP come from two aspects: one is the internal micro-level productivity increase brought about by technological progress within enterprises, which stems from technological innovation, R&D investment, deepening division of labor, improvement in management level, and optimization of internal resource allocation. The other is the improvement of resource allocation efficiency between enterprises, where production factors flow from enterprises with low productivity to those with high productivity. If high-productivity enterprises have a lower market share, it indicates that factors have not been effectively allocated to high-productivity enterprises, leading to low resource allocation efficiency between enterprises. This paper decomposes TFP into three parts: enterprise micro-level productivity, labor factor allocation efficiency, and capital factor allocation efficiency, to explore the impact of the synergy between digital technology innovation and green technology innovation on enterprise total factor productivity.

From the perspective of enterprise internal micro-level productivity, enterprises can use digital technology for automated production, digital monitoring of the production process [28], real-time adjustment of production plans, optimization of production processes, and the adoption of clean energy instead of traditional energy sources in order to implement recycling and resource-saving measures. This helps enterprises reduce energy consumption, lower pollutant emissions, and minimize resource waste, thereby reducing internal production costs and improving production efficiency. On one hand, digital technology innovation promotes the real-time and transparent progress of key activities such as production processes, R&D processes, financial control, and logistics management processes, which is beneficial for timely communication and effective analysis of information between different departments within the enterprise, reducing internal coordination and communication costs, and thus improving the efficiency of integrated management decision-making [29]. It also strengthens communication between different individuals or departments within the enterprise, reducing internal information blockages and promoting information flow and resource sharing between departments. Enterprises can allocate existing resources to the departments that need them most, achieving optimized internal resource allocation.

The impact of technological innovation on labor is mainly reflected in improving labor productivity, changing labor methods and demand, and creating new job opportunities. Through technological innovation, new production tools and methods are introduced, requiring workers to continuously learn new skills and knowledge to adapt to market demands, enabling workers to complete tasks more quickly and accurately. With the development of machinery and automation technology, some traditional labor positions may be replaced by machines, but at the same time, new job positions will also be created, such as a large number of technical talents needed in high-tech fields and emerging industries [30]. The intelligent development of enterprises will form a substitution of advanced machinery and equipment for low-skilled labor [31], which will further reduce the demand for low-skilled labor [32]. Highly educated labor has strong professional knowledge and skills in the field of digital and green technology innovation and can better cope with the challenges of technological changes and market demands. Enterprises will increase the demand for highly skilled professionals, optimize the structure of corporate human capital, and improve the efficiency of labor allocation for corporate innovation capabilities, thereby promoting the enhancement of total factor productivity.

From the perspective of capital factor allocation efficiency, technological innovation can improve the efficiency of capital allocation by reducing external transaction costs, improving investment decision efficiency, and financing allocation efficiency. The characteristics of digital technology, such as easy dissemination, strong replicability, and low marginal costs, make it easier for enterprises to obtain external information, reducing the communication costs between enterprises and the market, and thus reducing the costs of external transactions for enterprises. Digital technology has broadened the channels through which enterprises obtain information and improved their information analysis capabilities, providing strong support for corporate investment activities [33,34]. Enterprises can access a wider range of upstream and downstream companies, which is conducive to comparing and screening potential transaction counterparts, promoting interconnection and efficient collaboration between various links of the industrial chain, and helping to optimize management investment decisions. Secondly, in the field of technological innovation, R&D projects usually require a large amount of financial support, and the investment return period is long and uncertain, so this field faces constraints in various aspects such as financial resources. With the help of precise identification through technologies such as big data and cloud computing, it can promote financial product innovation and improve service efficiency, providing financing channels and convenience for these enterprises [35], thereby improving the efficiency of capital financing allocation and helping to promote the transformation and upgrading of the industry in the direction of green and clean development. It can meet the needs of green economic development.

Based on the above analysis, this paper proposes the following research hypotheses:

H2: *Digital–green collaborative technological innovation enhances the TFP of enterprises by improving their micro-level production efficiency.*

H3: *Digital–green collaborative technological innovation enhances the TFP of enterprises by optimizing labor factor allocation efficiency.*

H4: *Digital–green collaborative technological innovation enhances the TFP of enterprises by optimizing capital factor allocation efficiency.*

Figure 1 illustrates the theoretical mechanism proposed in this study. Digital–green collaborative technological innovation first operates inside the production system by improving process monitoring, cleaner production, and resource-use efficiency. It then affects

the allocation system by reshaping the matching of labor skills and capital investment toward firms with stronger green competitive advantages. In this sense, the figure connects the systems perspective with the three hypotheses on micro-level productivity, labor allocation efficiency, and capital allocation efficiency.

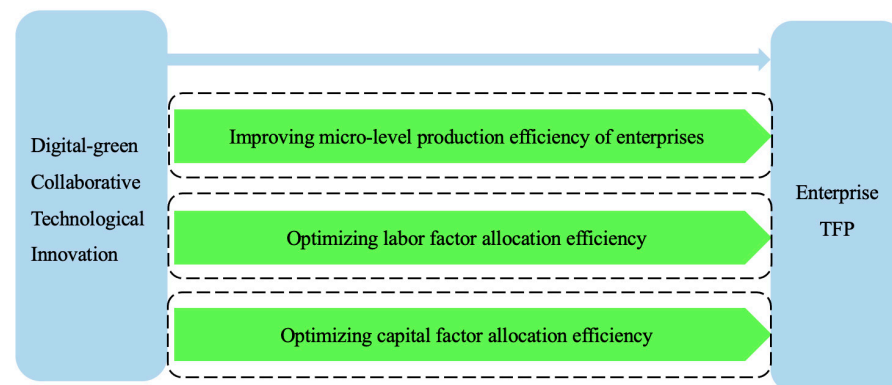


Figure 1. The Mechanism of Digital-green collaborative technological innovation on enterprise TFP.

4. Empirical Research Design

4.1. Sample Selection and Data Sources

This paper selects Chinese A-share listed companies from 2008 to 2022 as the initial research sample. The sample company data comes from the CSMAR database. Information related to corporate invention patents comes from the WinGo financial text data platform and the State Intellectual Property Office of the People’s Republic of China. After processing the relevant variables involved in this paper and matching the two databases, the initial sample is processed as follows: (1) Remove samples of ST-listed companies; (2) Remove samples from the financial industry; (3) Remove samples where total assets are less than total liabilities; (4) Remove samples of enterprises younger than one year; (5) Exclude data from the year of IPO and prior years; (6) Perform a 1% tail trimming for continuous variables. After organization, this paper ultimately obtains a total of 24,405 sample observations at the enterprise-year level from 2008 to 2022.

4.2. Variable Definition

4.2.1. Core Explanatory Variable: Synergy Between Digital Technology Innovation and Green Technology Innovation

Existing literature typically employs textual analysis of annual reports from listed companies to characterize corporate digital transformation or digital technology levels [36]. With the introduction of policy standards for digital and green development, recent studies have begun utilizing IPC codes [37] and patent text content [38] to construct relevant indicators. Following this approach and referring to the 2023 Digital Transformation Trend Report and official documents, this paper extracts keywords such as “underlying technology,” “technological application,” “cloud platform,” and “smart factory.” We perform textual analysis on corporate patent applications to identify and calculate the annual volume of digital economy patent applications. The measure for digital technological innovation, denoted as *Diginno*, is calculated as the natural logarithm of the application count plus one. Simultaneously, we use the number of green patent applications by listed companies (log-transformed) as *Greinnno* to measure the level of green technological innovation [39].

The essence of digital technology empowering green technology lies in utilizing big data to optimize production processes, improve energy efficiency, and reduce emissions through comprehensive data processing, thereby achieving sustainable development. The “dual-transformation” synergy (digitization leading greening, and greening driving dig-

itization) is the core path of current development. This paper constructs an interaction term ($Interact = Diginno \times Greinno$) as the core explanatory variable to measure the synergy between digital and green technological innovation.

More specifically, the interaction term is designed to separate digital–green collaboration from the simple scale effect of innovation. A firm with only digital patents or only green patents may have strong single-domain innovation, but its Interact value remains limited because the two knowledge bases have not been combined. A higher Interact value appears only when digital and green innovation activities are both present and increase together. This measurement choice is consistent with the systems view adopted in this study: collaboration is observed through the joint development of complementary technological subsystems rather than through the absolute number of patents in one domain alone. At the same time, we acknowledge that patent-based interaction cannot fully observe informal coordination, managerial learning, or cross-department routines inside firms. Therefore, the variable is interpreted as a measurable proxy for technological complementarity, not as a complete record of all organizational collaboration.

4.2.2. Enterprise Total Factor Productivity

TFP is a core indicator for measuring high-quality micro-enterprise development, reflecting output growth driven by technological progress, management optimization, and resource allocation efficiency after accounting for traditional inputs like capital and labor. In the baseline regression, this paper employs the Ordinary Least Squares (OLS) method to estimate the Cobb–Douglas production function: total output is measured by operating income, capital input by net fixed assets, labor input by the total number of employees, and intermediate inputs by operating costs. Considering the potential simultaneity bias between factor inputs and productivity, we further utilize the LP (Levinsohn–Petrin) and OP (Olley–Pakes) methods in robustness checks to re-estimate TFP, mitigating endogeneity issues and ensuring the credibility of the conclusions.

4.2.3. Control Variables

The paper selected a series of control variables (Controls) at the enterprise level to reduce the impact of other potential factors on the empirical results. Specifically, it includes: (1) Firm Age: controls for the impact of accumulated technical expertise (measured as the natural logarithm of the difference between the accounting year and the founding year plus one); (2) The proportion of the largest shareholder: reflects the monitoring or inhibiting effect of ownership concentration on innovation (measured as the percentage of shares held by the largest shareholder); (3) Board size: reflects decision-making expertise and coordination costs (measured as the natural logarithm of the number of directors); (4) Current ratio: reflects financial security supporting long-term innovation (measured as the ratio of current assets to total assets); (5) Profitability: reflects the sufficiency of internal cash flow (measured as the ratio of net profit to operating income); (6) Return on assets: reflects overall operational efficiency (measured as the ratio of net profit to total assets); (7) The proportion of independent directors: controls for agency problems to optimize innovation allocation (measured as the proportion of independent directors on the board); (8) Property rights nature: controls for heterogeneity in policy support between state-owned (SOE) and non-state-owned enterprises (Non-SOEs) (indicator variable: 1 for SOEs, 0 otherwise).

4.3. Model Construction

To examine the impact of the synergy between digital technology innovation and green technology innovation on enterprise total factor productivity, this paper constructs the following model (1) for baseline regression testing:

$$TFP_{it} = \alpha_0 + \alpha_1 Interact + \sum Controls + \sum Firms + \sum Year + \sum Province \times Year + \varepsilon_{it} \quad (1)$$

In model (1), i represents the enterprise, t represents the year, and the dependent variable TFP_{it} represents the total factor productivity of enterprise i in year t . The core explanatory variable *Interact* represents the synergy between digital technology innovation and green technology innovation. Controls represent a series of control variables at the enterprise level and *Firms* represents firm fixed effects, controlling for time-invariant individual characteristics (e.g., corporate culture, initial management traits). *Year* represents year fixed effects, capturing macroeconomic shocks and cyclical fluctuations. *Province* $\times$ *Year* represents the interaction between region and year fixed effects, aimed at excluding differences in policy environments or regional economic fluctuations evolving over time. ε_{it} is the random error term.

This paper focuses on the coefficient a_1 of *Interact*. If a_1 is significantly positive, it indicates that the synergy between digital and green technological innovation significantly enhances corporate TFP, thereby validating the theoretical expectations of this study.

For this reason, the empirical interpretation is deliberately cautious. A positive coefficient of *Interact* means that the productivity effect associated with digital innovation becomes stronger when green innovation is also present, and vice versa. It does not mean that every firm automatically realizes synergy once it owns both types of patents. In practice, the conversion from technological complementarity to productivity improvement still depends on managerial coordination, data infrastructure, employee skills, financing conditions, and the institutional environment. This explanation also helps connect the econometric design with the systems framework: the coefficient captures one observable outcome of interaction among technological, organizational, and institutional subsystems.

5. Empirical Results and Analysis

5.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables of this paper. The mean of the enterprise total factor productivity (TFP_OLS) is 11.036 with a standard deviation of 1.233, indicating a significant variation in total factor productivity among different enterprises. The median value of the variable *Interact* is 0, suggesting that the current level of synergy between digital technology and green technology in listed companies is relatively low and requires further enhancement and strengthening. The statistical information for other control variables is similar to previous studies.

Table 1. Descriptive Statistics of Main Variables.

Variables	Observations	Mean	Standard Deviation	Minimum	Median	Maximum
TFP_OLS	24,405	11.0360	1.2330	8.2010	10.9020	14.4690
Greinno	24,405	0.3690	0.7430	0.0000	0.0000	3.7610
Interact	24,405	0.7990	2.2360	0.0000	0.0000	19.2500
Diginno	24,405	0.7520	1.1790	0.0000	0.0000	5.1820
Age	24,405	2.8240	0.3550	1.6090	2.8900	3.4660
OwnCon1	24,405	34.2630	14.5870	9.0870	32.1300	74.0000
Board	24,405	2.1480	0.1690	1.7920	2.1970	2.7080
Liquid	24,405	0.5700	0.1890	0.10400	0.5790	0.9500
Return	24,405	0.0710	0.1260	−0.9110	0.0640	0.4850
Roa	24,405	0.0390	0.0520	−0.2470	0.0370	0.2000
Indedir	24,405	37.3020	5.2530	27.2700	33.3300	57.1400
State	24,405	0.3590	0.4800	0.0000	0.0000	1.0000

5.2. Benchmark Regression Test

Table 2 presents the benchmark regression results examining the impact of digital and green technology innovations on corporate performance. As indicated, the regression coefficient of the Interact between digital and green technologies remains significantly positive, suggesting that the coexistence and interaction of digital and green innovation activities are associated with higher TFP. This result is interpreted as evidence of technological complementarity rather than conclusive proof of all dimensions of synergistic value creation. In other words, the interaction term indicates that firms combining digital and green innovation obtain additional productivity advantages relative to firms relying on either dimension alone, while the organizational and managerial processes behind this complementarity require further qualitative and cross-country research.

Table 2. Benchmark Regression Results.

Variables	(1) TFP_OLS	(2) TFP_OLS	(3) TFP_OLS	(4) TFP_OLS	(5) TFP_OLS	(6) TFP_OLS
Interact	0.0616 *** (0.0027)	0.0138 *** (0.0022)	0.0131 *** (0.0022)	0.0128 *** (0.0022)		
Diginno					0.0198 *** (0.0052)	
Greinnno						0.0339 *** (0.0064)
Control Variables	No	Yes	Yes	Yes	Yes	Yes
Enterprise Effect	No	Yes	Yes	Yes	Yes	Yes
Year Effect	No	No	Yes	Yes	Yes	Yes
Region × Year Effect	No	No	No	Yes	Yes	Yes
Observations	24,405	24,405	24,405	24,405	24,405	24,405
R ²	0.0191	0.4210	0.4340	0.4590	0.4590	0.4590

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$. If the regression results of the main variables are decimals, they are retained to three significant figures after the decimal point; otherwise, they are accurate to four decimal places. The subsequent tables have the same format.

To further delineate the complementarity effect from the impacts of individual technological innovations, we separately analyze digital technology innovation (Diginno) and green technology innovation (Greinnno). Column (5) shows that the coefficient for Diginno is 0.0198 (significant at the 1% level). This result is consistent with the findings that reported a coefficient of 0.0295 using the Olley-Pakes (OP) method [38], thus reinforcing the reliability of our estimates. Column (6) indicates that the coefficient for Greinnno is 0.0339, also significant at the 1% level. These results confirm that both digital and green innovations independently contribute to TFP enhancement. When Column (4) is compared with Columns (5) and (6), the significantly positive coefficient of the interaction term further suggests that the joint presence of digital and green innovation is associated with an additional productivity advantage. We interpret this result as evidence of technological complementarity. It should not be read as definitive proof that every firm automatically realizes a full synergistic value-creation process, because such a process also depends on internal coordination, managerial capacity, and the external institutional environment.

This comparison also responds to the concern that the estimated effect may simply reflect firms' general innovation capacity. If the result were driven only by innovation scale, the separate digital and green innovation variables would be sufficient to explain productivity gains. The persistence of a positive interaction effect suggests that the two types of innovation play complementary roles. Digital tools can make green R&D more measurable and scalable, while green objectives provide concrete application scenarios for digital technologies. The estimated result should therefore be understood as evidence

that the combination of these two directions matters for firm transformation, although the precise organizational routines behind the combination remain a promising topic for future case-based research.

5.3. Robustness Test

5.3.1. Instrumental Variable Test

The regression results may be affected by endogeneity issues, which could be due to reverse causality. Therefore, this paper draws on existing literature to use the lagged explanatory variables by one period [40] and postal and telecommunications data to construct instrumental variables [38]. First, this paper uses the interaction term of the lagged one-period digital technology innovation and green technology innovation of listed companies as the instrumental variable. The synergy between digital technology and green technology innovation of the previous year is related to the synergy development of the current year for the enterprise, but the TFP of the enterprise in the current year is mainly influenced by the synergy development of digital technology and green technology innovation of the enterprise in the current year, and it is hardly affected by the synergy development of the previous year's digital technology and green technology innovation. This meets the exogeneity and relevance conditions required for the selection of instrumental variables.

Second, this paper uses postal and telecommunications data to construct instrumental variables. On the one hand, the development and application of digital technology and green technology are closely related to the improvement of postal and telecommunications infrastructure. The communication methods in the area where the enterprise is located may affect the technological development process of local enterprises in various aspects [41]. Since the Plain Old Telephone Network (PSTN) was once one of the main network access methods in our country, the number of fixed telephones per million people in 1984 can reflect the development process of the postal and telecommunications industry. On the other hand, the use frequency of fixed telephones in the daily business activities of the enterprise has decreased significantly, and the impact on the TFP of the enterprise has gradually disappeared, making the exclusivity requirement of the instrumental variable better met. At the same time, considering that using a single-year variable in the fixed effects model may have a problem that cannot be measured. In summary, this paper uses the interaction item of the number of fixed telephones per million people in 1984 and the number of internet access ports per capita at the city level of the previous year as the instrumental variable for the enterprise to carry out the synergy of digital technology innovation and green technology innovation (Fix Tel) [42]. The first column shows that the regression coefficients of the two instrumental variables are significantly positive, indicating that they meet the relevance requirements. The second column of Table 2 shows that the coefficient of the explanatory variable Interact is positive and significant at the 1% level, indicating that after controlling for potential endogeneity, the baseline conclusion of this paper still holds.

5.3.2. Replace the Explanatory Variables with Lagged Terms

Since the enhancement effect of the synergy between digital technology innovation and green technology innovation on TFP may have a time lag, this paper re-conducts the baseline regression using the lagged one period of the explanatory variables. As can be seen from column (1) of Table 3, the regression coefficient is significantly positive, and the result is robust.

Table 4 summarizes four robustness checks designed to examine whether the baseline conclusion is sensitive to measurement choices, sample composition, sample period, or patent quality. Across these specifications, the coefficient of the core explanatory variable

remains significantly positive. This consistency indicates that the productivity-enhancing complementarity between digital and green technological innovation is not driven by a particular TFP estimation method, a specific industry group, a narrow sample window, or low-quality patent applications.

Table 3. Results of the instrumental variable test.

Variables	(1) Interact	(2) TFP_OLS
L_Interact	0.4199 *** (0.0276)	
FixTel	0.2421 * (0.1463)	
Interact		0.0276 *** (0.0106)
Control Variables	Yes	Yes
Enterprise Effect	Yes	Yes
Year Effect	Yes	Yes
Observations	14,025	14,025

* $p < 0.05$, *** $p < 0.001$.

Table 4. Robustness Check.

Variables	(1) TFP_OLS	(2) TFP_OP	(3) TFP_LP	(4) TFP_OLS	(5) TFP_OLS	(6) TFP_OLS
L_Interact	0.0090 *** (0.002)					
Interact		0.0038 ** (0.0018)	0.0071 *** (0.0020)	0.0132 *** (0.0023)	0.0133 *** (0.0019)	
Interact_quati						0.0154 *** (0.0030)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Region $\times$ Year Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,603	24,405	24,405	22,999	27,809	24,405
R ²	0.4480	0.4020	0.4250	0.4650	0.4450	0.4580

** $p < 0.01$, *** $p < 0.001$.

5.3.3. Replace the TFP Indicator

This paper recalculates the TFP of enterprises using the LP method and the OP method to replace the explained variable indicator. After the replacement, as can be seen from columns (2) to (3) of Table 4, the regression coefficients of the synergy between digital technology innovation and green technology innovation are both significantly positive, and the results are robust.

5.3.4. Exclude Samples from the Communications and Information Technology Industries

Due to the high technological foundation and R&D level of listed companies in the communications and information technology industries, they have more advantages in technological innovation compared to other enterprises. Therefore, to reduce the impact of extreme values on the results of this paper, this paper excludes enterprise samples classified in the industries of software and information technology services, internet and related services, and telecommunications, broadcasting, satellite transmission, and related services. After conducting the baseline regression, column (4) of Table 4 shows that the regression coefficient of the core explanatory variable is significantly positive, and the result is robust.

5.3.5. Expand the Sample Period

Considering that expanding the sample size can reduce the impact of sampling errors and improve the accuracy and reliability of statistical analysis, this paper uses listed enterprises from 2003 to 2022 to expand the sample period. As can be seen from column (5) of Table 4, the regression coefficient of the core explanatory variable is significantly positive, and the baseline regression results are still consistent with the conclusions above, and the results are robust.

5.3.6. Replacing the Explanatory Variable: Addressing Measurement Bias in Patent Quality

Relying solely on the number of patent applications as a proxy for technological innovation may not fully capture the actual output value and technological sophistication of innovative activities. Against the backdrop of the synergy between digitalization and greenization, low-quality “strategic innovation” is prone to introducing measurement bias, thereby compromising the accuracy of estimation results. To mitigate the potential interference of indicator selection on the research findings, this study draws on existing literature [43] and re-conducts the regression analysis by employing the interaction term of digital technology invention patents and green technology invention patents ($\text{Interact_quati} = \text{Diginno_Inv} \times \text{Greinno_Inv}$) as the proxy variable for patent quality. Compared with utility model patents and design patents, invention patents undergo more rigorous examination procedures and impose higher requirements on novelty, inventiveness, and practicality, thus serving as a more reliable indicator of high-quality technological breakthroughs.

Column (6) of Table 4 reports the regression results after replacing the explanatory variable. It is evident that the regression coefficient of the core explanatory variable remains significantly positive at the 1% statistical level. This finding demonstrates that the complementarity effect of digital technological innovation and green technological innovation persists robustly even when accounting for the dimension of patent quality, thereby validating the strong robustness of the baseline regression conclusions.

5.4. Heterogeneity Analysis

5.4.1. Heterogeneity of Corporate Ownership

To examine how ownership structures influence the impact of digital–green technological synergy on TFP, the sample is bifurcated into State-Owned Enterprises SOEs and non-SOEs. Regression results in columns (1) and (2) of Table 5 reveal that the coefficient for the core explanatory variable is statistically insignificant for SOEs. Conversely, the coefficient for non-SOEs is significantly positive at the 1% level, suggesting that the synergy between digital and green innovation predominantly drives productivity gains in the private sector.

Several institutional and market-based factors underpin this divergence. First, SOEs often benefit from preferential access to government subsidies, credit resources, and tax incentives. These “soft budget constraints” may inadvertently diminish the urgency for radical innovation and dampen employee initiative, hindering the firm’s ability to pivot rapidly toward market-driven technological frontiers. Second, non-SOEs, typically constrained by limited resource endowments and financing hurdles, operate under a “survival-induced” motivational framework. For these firms, the “dual transformation” (digital and green) is not merely a reactive measure to satisfy external regulatory legitimacy; it is an endogenous competitive strategy. By leveraging the technology spillover effects of digital–green synergy, non-SOEs can achieve “leapfrog development” despite resource scarcity. In contrast, SOEs may suffer from institutional inertia and a lack of market-driven incentives to efficiently translate innovation into tangible productivity growth.

Table 5. Heterogeneity Test.

Variable	(1) SOE TFP_OLS	(2) Non-SOE TFP_OLS	(3) Strong Intellectual Property Protection TFP_OLS	(4) Weak Intellectual Property Protection TFP_OLS	(5) Eastern TFP_OLS	(6) Central TFP_OLS	(7) Western TFP_OLS
Interact	0.0011 (0.0035)	0.0216 *** (0.0027)	0.0204 *** (0.0037)	0.0181 *** (0.0039)	0.0119 *** (0.0025)	0.0334 *** (0.0085)	0.0131 ** (0.0058)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region × Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8608	15,554	7234	9171	18,154	2695	3307
R ²	0.4810	0.5080	0.4740	0.4550	0.4430	0.4940	0.5170

** $p < 0.01$, *** $p < 0.001$.

5.4.2. Heterogeneity of Intellectual Property Rights (IPR) Protection

IPR protection provides the legal foundation for internalizing the returns on innovation. Robust IPR frameworks incentivize R&D investment and facilitate the commercial application of technological breakthroughs. This study categorizes regions into high and low IPR protection groups [38]. As shown in columns (3) and (4) of Table 5, the interaction term (Interact) remains significantly positive across both cohorts, but the magnitude of the coefficient is substantially larger in regions with stronger IPR protection.

The economic intuition is that IPR protection serves as an “incentive accelerator” for technological synergy. Digital technologies are inherently characterized by high liquidity and low imitation costs. In the absence of rigorous legal safeguards, green innovation outputs are highly vulnerable to “free-riding” by competitors. A stringent legal environment establishes a “safe harbor” for innovation, ensuring that firms can exclusively capture the efficiency dividends generated by digital–green integration. Consequently, in high-protection environments, firms are more inclined to utilize digital tools to undertake complex, high-risk green R&D, thereby amplifying the productivity multiplier effect.

5.4.3. Regional Heterogeneity

Given the marked disparities in economic development and innovation ecosystems across China, we perform baseline regressions for the Eastern, Central, and Western regions. The results in columns (5)–(7) of Table 5 indicate that while all regional coefficients are significantly positive, the effect size in the Central region is notably larger than in the Eastern region.

This phenomenon reflects the interplay between “demand-pull innovation” and “diminishing marginal returns.” As a primary hub for industrial relocation and heavy industry clusters, the Central region faces acute pressure from environmental regulations and the urgent need for energy efficiency upgrades. Here, digital–green synergy acts as a pivotal technological lever to decouple economic growth from high energy consumption and pollution. Therefore, the marginal productivity gains are more pronounced than in the Eastern region, where technological maturity is closer to the “frontier.” Meanwhile, although the Western region faces structural developmental hurdles, the dual-innovation synergy is increasingly emerging as a vital engine for catch-up growth, bolstered by national initiatives such as the “Western Development Strategy” and green compensation mechanisms.

6. Further Analysis

Decomposition of Total Factor Productivity

The text decomposes the productivity of industry i in province p by weighting according to the factor shares of enterprises [44].

$$\Omega_{pi} = \sum_i \theta_{fpi} \times \omega_{fpi} = \overline{\omega_{pi}} + \sum_i (\theta_{fpi} - \overline{\theta_{pi}}) \times (\omega_{fpi} - \overline{\omega_{pi}}) \quad (2)$$

In this context, ω_{fpi} represents the TFP of enterprise f , θ_{fpi} represents the factor share of enterprise f in industry i of province p , and $\overline{\omega_{pi}}$ represents the simple average productivity of all enterprises within industry i of province p . $\overline{\theta_{pi}}$ represents the simple average factor share of all enterprises within industry i of province p . The first term in equation (2) reflects the level of microeconomic productivity of enterprises, and the second term is the covariance between the factor share and productivity of enterprises, reflecting the efficiency of resource allocation among enterprises within industries in a province. The larger the value of this term, the higher the factor share obtained by enterprises with higher productivity, indicating higher resource allocation efficiency.

This paper uses the share of the average number of employees of enterprise f in the total number of employees of industry i in province p to represent the labor factor share θ_{fpil} obtained by enterprise f , obtaining the labor allocation efficiency Y_{pil} at the province-industry level.

$$Y_{pil} = \sum_i (\theta_{fpil} - \overline{\theta_{pil}}) \times (\omega_{fpi} - \overline{\omega_{pi}}) \quad (3)$$

This approach uses the share of the net fixed assets of enterprise f in the total fixed assets of industry i in province p to represent the capital share θ_{fpik} obtained by enterprise f , thereby deriving the resource allocation efficiency Y_{pik} at the provincial-industry level.

$$Y_{pik} = \sum_i (\theta_{fpik} - \overline{\theta_{pik}}) \times (\omega_{fpi} - \overline{\omega_{pi}}) \quad (4)$$

To examine the impact of the synergy between digital technology innovation and green technology innovation on the microeconomic productivity, labor factor, and capital factor allocation efficiency of enterprises, this paper constructs the following model (5) for mechanism testing:

$$(\overline{\omega_{pi}}/Y_{pil}/Y_{pik}) = \alpha_0 + \alpha_1 \overline{Interact} + \sum \overline{Controls} + \sum Year + \sum Province \times Year + \varepsilon_{it} \quad (5)$$

This paper uses $\overline{\omega_{pi}}$, Y_{pil} , Y_{pik} to represent the dependent variables, the core variable $\overline{Interact_{pi}}$ to represent the synergy between digital and green technology innovations within enterprises in industry i of province p . It also includes a series of control variables $\overline{Controls}$ at the enterprise level in industry i of province p . Year and Province $\times$ Year represent the year fixed effects and the interaction terms of region and year fixed effects, respectively.

Table 6 reports the results of the mechanism tests. The empirical evidence reveals that the synergy between corporate digital technology innovation and green technology innovation ($\overline{Interact_{pi}}$) yields regression coefficients for micro-level productivity, labor allocation efficiency, and capital allocation efficiency that are all significantly positive at the 1% level.

The mechanism results further clarify why the systems perspective is useful. The productivity effect is not transmitted through a single channel. Instead, it appears in the production subsystem, the labor-allocation subsystem, and the capital-allocation subsystem at the same time. In production, digital–green collaboration supports cleaner process control and more accurate resource monitoring. In labor allocation, it increases demand for workers who can combine data skills with environmental knowledge, thereby improving human–capital matching. In capital allocation, it helps investors and managers identify projects with both technological and environmental returns. These channels are interconnected. Better process data can improve financing decisions, and better financing can support further green-digital upgrading.

Regarding the effect cycle, these findings underscore the long-term driving nature of the digital–green synergy. While initial R&D and equipment expenditures may impose short-term cost pressures, the long-term integration allows digital technology to

empower green innovation. This synergy facilitates sustained productivity growth by optimizing production processes and reducing energy consumption. Specifically, the results in columns (1)–(3) indicate that a 1% increase in the synergy term is associated with a 13.66% rise in micro-level productivity, alongside increases of 14.54% and 17.82% in labor and capital allocation efficiencies, respectively. Notably, the magnitude of improvement in factor allocation efficiency significantly outweighs that of micro-level productivity, highlighting resource optimization as a core value driver.

Table 6. Results of Mechanism Testing.

Variables	(1) $\bar{\omega}_{pi}$	(2) Y_{pil}	(3) Y_{pik}
$\overline{Interact}_{pi}$	0.1366 *** (0.0057)	0.1454 *** (0.0054)	0.1782 *** (0.0063)
Control Variables	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes
Regional Effects	Yes	Yes	Yes
Observations	24,405	24,405	24,405
R ²	0.6240	0.4540	0.4930

*** $p < 0.001$.

Digital–green synergistic innovation does not function through a solitary technical channel; instead, it enhances TFP via a tripartite pathway: “technological progress, labor resource optimization, and capital resource optimization.” The underlying logic is that this synergy mitigates information asymmetry, enabling labor and capital to transcend industry barriers. Consequently, resources gravitate precisely toward high-efficiency firms possessing green competitive advantages, triggering a shift in micro-level growth drivers. Although potential mechanisms such as improved financing and optimized governance may also play a role, the three channels prioritized in this study are substantiated by both theoretical frameworks and empirical evidence, constituting the primary pathways for TFP enhancement.

7. Policy Implications and Future Research Directions

7.1. Conclusions

As China transitions toward a high-quality development paradigm, the synergy between digital and green technological innovations has emerged as a dual engine for industrial upgrading and the realization of national “dual-carbon” objectives (e.g., the 14th Five-Year Plan for Digital Economy Development). Utilizing a panel of Chinese A-share listed companies from 2008 to 2022, this study empirically investigates the impact of digital–green technological synergy on TFP and explores its underlying transmission mechanisms.

The empirical evidence yields three primary findings: First, the interaction between digital and green innovation is positively associated with corporate TFP, indicating a productivity-enhancing complementarity between the two technological domains. This positive correlation remains robust across various endogeneity treatments and sensitivity tests. Second, mechanism analysis indicates that this complementarity bolsters TFP through three critical channels: enhancing micro-level internal productivity, refining labor allocation, and optimizing capital efficiency, with the effect on factor allocation being the most salient. Third, heterogeneity tests reveal that the productivity-enhancing effects are significantly amplified in non-state-owned enterprises, central-region firms, and regions characterized by stronger intellectual property rights protection. This study advances the research framework on the relationship between technological innovation and firm productivity from the perspective of the digital–green dual drive in technological innovation. It addresses a

limitation of prior literature, where digital technological innovation and green technological innovation have often been examined in isolation, by investigating their combined impact and by identifying factor allocation efficiency as an important transmission channel.

7.2. Policy Implications

Based on these findings, this study offers the following implications for policymakers and corporate practitioners:

The policy implications are therefore not limited to encouraging more patents. For firms, the key task is to build internal interfaces between digital departments, R&D teams, environmental management units, and production lines. For governments, the key task is to improve the external conditions that make such interfaces valuable, including intellectual property protection, green finance, digital infrastructure, and skill-training systems. These suggestions follow directly from the heterogeneity and mechanism results: stronger IPR protection amplifies the productivity effect, and factor allocation efficiency is an important channel through which the effect is realized.

(1) Synergy-Driven Transformation Path and Governance Optimization of Digital–green Integration. Enterprises should strengthen the endogenous motivation for the integration of digital and green development, leverage digital technologies to reshape the entire green production chain at the foundational level, and convert technological dividends into productivity advantages. For example, firms can use industrial Internet platforms, energy-management systems, and digital supply-chain traceability tools to support cleaner production, green product design, and low-carbon logistics. Policymakers should establish a precisely enabling factor guarantee system: integrate green finance with digital technologies to guide capital flow accurately into high-efficiency projects and improve capital allocation efficiency; rely on compound skill training to facilitate the orderly transition of the labor force to green jobs; and support data-sharing infrastructure that lowers the cost of digital–green experimentation for small and medium-sized enterprises. Governments should also construct a balanced and inclusive urban governance framework and accelerate the equalization of regional digital infrastructure to lower the threshold for transformation.

(2) Implementing Targeted and Differentiated Incentive Schemes. For SOEs, it is imperative to recalibrate innovation assessment frameworks to incentivize leadership in high-stakes digital–green technological breakthroughs. For non-SOEs, the focus should shift toward optimizing the business environment, strengthening intellectual property protection, and mitigating institutional transaction costs to empower them as flexible pioneers in market-driven technological integration. Furthermore, for the Central and Western regions, regional innovation funds and industry-university-research alliances should be prioritized to enhance technology absorption and spillover capacities. Local governments can operationalize these policies by linking subsidies and tax incentives to verifiable digital–green outputs, such as green invention patents, energy-saving digital applications, and improvements in factor allocation efficiency.

7.3. Limitations and Future Research

While this research provides valuable insights into the complementary effects of dual innovations, several limitations warrant further investigation. First, due to data constraints, innovation was primarily quantified using patent counts. Although patent data provide an observable and comparable indicator, they cannot fully capture the quality of innovation, non-patented process improvements, or the depth of organizational collaboration between digital and green teams. Future studies could employ multi-dimensional metrics, such as patent quality, technological conversion rates, survey-based measures of collaboration, or textual evidence from annual reports. Second, as this study focuses exclusively on Chinese

A-share listed companies, the generalizability of these findings to small and medium-sized enterprises, unlisted firms, other emerging economies, or different institutional settings remains an open question for comparative research. Third, the interaction-term approach identifies statistical complementarity but cannot directly observe all internal coordination processes or causal micro-mechanisms. Future research could combine econometric analysis with case studies, interviews, or cross-country comparisons to examine how different systems of regulation, finance, intellectual property protection, and labor markets condition digital–green collaboration. Finally, while this study adopts a micro-firm perspective, future research could transition to a meso-level analysis, exploring how industrial chain collaborations and innovation clusters catalyze regional green transitions through multi-stakeholder interactions.

Author Contributions: B.Q. provided the idea and overall direction of this article and made contributions to the revision of the article structure in the later stage; X.Y. is mainly responsible for the acquisition of data and the writing of the manuscript; Y.Y. made careful revisions and arrangement of the article data; J.G. revised the manuscript.; and H.Z. drew the images and tables in the article. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Shanghai Philosophy and Social Science Planning Project [grant number 2024BJL002].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Lin, B.; Zhu, Y. Supply chain configuration and total factor productivity of renewable energy. *Renew. Sustain. Energy Rev.* **2025**, *209*, 115140. [\[CrossRef\]](#)
2. Jia, W.; Zhang, Z.; Su, B.; Sun, Y.F.; Yu, S. Impact of local government environmental attention on corporate total factor productivity: Evidence from 288 Chinese cities. *J. Environ. Manag.* **2025**, *374*, 124052. [\[CrossRef\]](#)
3. Gora, K.; Yadav, M. A bibliometric analysis on the role of corporate governance in micro, small and medium enterprises. *Corp. Gov. Int. J. Bus. Soc.* **2025**, *25*, 992–1015.
4. Cui, J. Exploring the impact of digital leadership and green digital innovation on corporate digital transformation. *J. Curr. Soc. Issues Stud.* **2025**, *2*, 215–220. [\[CrossRef\]](#)
5. Holmström, J. Recombination in digital innovation: Challenges, opportunities, and the importance of a theoretical framework. *Inf. Organ.* **2018**, *28*, 107–110. [\[CrossRef\]](#)
6. Halim-Lim, S.A.; Jamaludin, A.A.; Islam, A.T.; Weerabahu, S.; Priyono, A. Unlocking potential for a circular bioeconomy transition through digital innovation, lean manufacturing and green practices: A review. *Manag. Environ. Qual. Int. J.* **2025**, *36*, 130–154.
7. Qiao, Y.; Li, X.; Hu, J. From digital to innovative: How does digital transformation affect corporate innovation? *Econ. Lett.* **2025**, *247*, 112210. [\[CrossRef\]](#)
8. Chen, Y.; Guo, H. Corporate performance: Green supply chain management, digital transformation and carbon neutrality. *Manag. Decis.* **2025**, *63*, 2432–2451.
9. Zhang, L.; Song, Z. Digital transformation, green technology innovation and corporate value. *Front. Environ. Sci.* **2025**, *13*, 1485881. [\[CrossRef\]](#)
10. Che, Z.; Wu, C.; Qu, W.; Zhang, N. How does multidimensional interaction of knowledge transfer affect digital innovation capability? *Knowl. Manag. Res. Pract.* **2025**, *23*, 13–25.
11. Mancuso, I.; Petruzzelli, A.M.; Panniello, U.; Vaia, G. Business model innovation in the banking sector: How digital technologies transform innovation drivers in value mechanisms innovations. *J. Eng. Technol. Manag.* **2025**, *75*, 101858. [\[CrossRef\]](#)
12. Chen, S.; Xiao, Y.; Zhang, Z. Resource regulation and green innovation: Evidence from China's water rights trading policy. *Environ. Res.* **2024**, *258*, 119443. [\[CrossRef\]](#) [\[PubMed\]](#)

13. Xu, W.; Li, M. Green tax system and corporate carbon emissions—a quasi-natural experiment based on the environmental protection tax law. *J. Environ. Plan. Manag.* **2025**, *68*, 2092–2122.
14. Fan, M.; Liu, W.; Yao, D. The impact of green finance reform and innovation pilot zones on corporate pollution and carbon reduction: From the perspective of dual objective constraints. *J. Environ. Manag.* **2025**, *389*, 126110. [[CrossRef](#)]
15. Gao, X.; Latif, B.; Ong, T.S.; Zhang, Q.; Yusri, Y. ESG performance and corporate competitiveness: The roles of green innovation, industry competition and media attention. *Stud. Econ. Financ.* **2025**, *43*, 740–761. [[CrossRef](#)]
16. Deng, J.; Li, Y.; Ding, Y.; Liu, F. Effect of media attention on corporate green technology innovation: Mechanism and evidence from China. *Empir. Econ.* **2025**, *68*, 697–727.
17. Yin, S.; Zhang, N.; Ullah, K.; Gao, S. Enhancing digital innovation for the sustainable transformation of manufacturing industry: A pressure-state-response system framework to perceptions of digital green innovation and its performance for green and intelligent manufacturing. *Systems* **2022**, *10*, 72. [[CrossRef](#)]
18. Zhou, Q.; Wang, S.; Ma, X.; Xu, W. Digital technologies and corporate green innovation: Opening the “black box” of resource orchestration mechanisms. *Sustain. Account. Manag. Policy J.* **2024**, *15*, 884–912. [[CrossRef](#)]
19. Hao, X.; Miao, E.; Wen, S.; Xue, Y.; Wu, H. Digital tsunami and the green wave: How R&D steers enterprise innovation towards sustainability. *Environ. Dev. Sustain.* **2025**, 1–26. [[CrossRef](#)]
20. Geels, F.W. Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. *Res. Policy* **2002**, *31*, 1257–1274. [[CrossRef](#)]
21. Markard, J.; Raven, R.; Truffer, B. Sustainability transitions: An emerging field of research and its prospects. *Res. Policy* **2012**, *41*, 955–967. [[CrossRef](#)]
22. Nambisan, S.; Lyytinen, K.; Majchrzak, A.; Song, M. Digital innovation management: Reinventing innovation management research in a digital world. *MIS Q.* **2017**, *41*, 223–238. [[CrossRef](#)]
23. Kivimaa, P.; Kern, F. Creative destruction or mere niche support? Innovation policy mixes for sustainability transitions. *Res. Policy* **2016**, *45*, 205–217. [[CrossRef](#)]
24. Porter, M.E.; van der Linde, C. Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [[CrossRef](#)]
25. Aghion, P.; Howitt, P. A Model of Growth Through Creative Destruction. *Econometrica* **1992**, *60*, 323–351. [[CrossRef](#)]
26. Henderson, R.M.; Clark, K.B. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Adm. Sci. Q.* **1990**, *35*, 9–30. [[CrossRef](#)]
27. Hsieh, C.; Klenow, P. Misallocation and Manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. [[CrossRef](#)]
28. Yoo, Y.; Boland, R.J., Jr.; Lyytinen, K.; Majchrzak, A. Organizing for Innovation in the Digitized World. *Organ. Sci.* **2012**, *23*, 1398–1408. [[CrossRef](#)]
29. Guo, L.; Xu, L. The effects of digital transformation on firm performance: Evidence from China’s manufacturing sector. *Sustainability* **2021**, *13*, 12844. [[CrossRef](#)]
30. Acemoglu, D.; Restrepo, P. The race between man and machine: Implications of technology for growth, factor shares, and employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [[CrossRef](#)]
31. Webb, M. The Impact of Artificial Intelligence on the Labor Market. SSRN Working Paper. 2019. Available online: <https://ssrn.com/abstract=3482150> (accessed on 6 June 2026).
32. Raj, M.; Seamans, R. Artificial intelligence, labor, productivity, and the need for firm-level data. In *The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press: Chicago, IL, USA, 2018; pp. 553–565.
33. Vial, G. Understanding digital transformation: A review and a research agenda. *J. Strateg. Inf. Syst.* **2019**, *28*, 118–144. [[CrossRef](#)]
34. Acemoglu, D.; Restrepo, P. Automation and new tasks: How technology displaces and reinstates labor. *J. Econ. Perspect.* **2019**, *33*, 3–30. [[CrossRef](#)]
35. Abbas, J.; Balsalobre-Lorente, D.; Amjid, M.A.; Al-Sulaiti, K.; Al-Sulaiti, I.; Aldereai, O. Financial innovation and digitalization promote business growth: The interplay of green technology innovation, product market competition and firm performance. *Innov. Green Dev.* **2024**, *3*, 100111. [[CrossRef](#)]
36. Wu, F.; Hu, H.Z.; Lin, H.Y.; Ren, X.Y. Enterprise digital transformation and capital market performance—Empirical evidence from stock liquidity. *Manag. World* **2021**, *37*, 130–144. (In Chinese)
37. Tao, F.; Wang, X.R.; Xu, Y.; Zhu, P. Digital transformation, industrial chain and supply chain resilience, and enterprise productivity. *China Ind. Econ.* **2023**, *5*, 118–136. (In Chinese)
38. Huang, B.; Li, H.; Liu, J.; Lei, J. Digital technology innovation and high-quality development of Chinese enterprises: Evidence from enterprise digital patents. *Econ. Res.* **2023**, *58*, 97–115. (In Chinese)
39. Xu, B.; Lin, B. How does green credit effectively promote green technology innovation? *Int. Rev. Financ. Anal.* **2025**, *102*, 104089. [[CrossRef](#)]
40. Li, M.; Zhao, Y.; Yan, J.; Huang, Y. Enterprise Digital Transformation and Green Technology Innovation: Evidence from Innovation Sub-Dimension and Time Lag Effect. *Pol. J. Environ. Stud.* **2025**, *34*, 177–186.

41. Huang, Q.H.; Yu, Y.Z.; Zhang, S.L. Internet development and manufacturing productivity improvement: Internal mechanism and Chinese experience. *China Ind. Econ.* **2019**, *8*, 5–23. (In Chinese)
42. Nunn, N.; Qian, N. US food aid and civil conflict. *Am. Econ. Rev.* **2014**, *104*, 1630–1666. [[CrossRef](#)]
43. Li, W.J.; Zheng, M.N. Substantive innovation or strategic innovation? The impact of macro-industrial policy on micro-enterprise innovation. *Econ. Res. J.* **2016**, *51*, 60–73. (In Chinese)
44. Wang, H.C.; Zhang, W.H.; Xia, Z.Y. Industrial scale preference and TFP of enterprises—Evidence from the text of five-year plans of provincial governments. *Econ. Res. J.* **2023**, *58*, 153–171. (In Chinese)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.