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Digital Optimization, Green R&D Collaboration, and Green Technological Innovation in Manufacturing Enterprises

Changchun Li [1] and Sen Wang [2,*]

[1] Business School, University of International Business and Economics, Beijing 100029, China
[2] School of Management, Beijing Union University, Beijing 100101, China
* Correspondence: gltwangsen@buu.edu.cn

Abstract: Manufacturing enterprises are confronted with the historic opportunity and challenge of balancing green transformation with economic development to achieve the goal of carbon neutrality. Some advanced companies are increasingly pursuing green development and innovation by expanding and optimizing the use of digital technology. In this study, we employ Chinese listed manufacturing companies from 2013–2019 as the research sample and examine the mechanism by which corporate digital optimization affects green technological innovation, as well as the mediating role of green R&D collaboration between the two. We also introduce external environmental orientation as a moderating variable. The results of fixed-effect Poisson model analysis are as follows. First, a positive correlation between digital optimization and green R&D collaboration indicates that scaling up digital optimization promotes green R&D collaboration. Second, we observe an inverted U-shaped relationship between green R&D collaboration and green technological innovation. Third, green R&D collaboration acts as a mediating factor between digital optimization and green technological innovation, and external environmental orientation moderates the relationship between digital optimization and green R&D collaboration. Fourth, the threshold effect results indicate that the optimal value of digital optimization projects is 10.167, with too many or too few projects impairing the effect of digital optimization on green technological innovation. All of the above results passed the robustness test.

Keywords: data optimization; external environmental orientation; green R& D collaboration; green technological innovation

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1. Introduction

Since the emergence of low-carbon development as a new strategy for achieving sustainable economic growth [1], green business practices have become a key research focus worldwide. At the United Nations General Assembly in September 2020, President Xi Jinping declared that "China would achieve carbon peaking by 2030 and carbon neutrality by 2060", emphasizing that the research and application of green technologies should be vigorously developed to achieve carbon neutrality as soon as possible. However, these plans are hindered by limited resources for implementation [2]; thus, manufacturing organizations in China now face the challenge of effectively encouraging green technological innovation (GTI).

The rapid development of digital technology has increased opportunities for organizations to accelerate environmental protection and encourage green product innovation. For example, Huawei Digital Energy, which has extensive knowledge of power electronics and digital technology, actively assists telecom operators in developing low-carbon sustainability through the Smart Power Project. By implementing projects such as "minimalist sites and modular power supplies", 325 billion kWh of green energy will be generated and 10 billion kWh of energy will be saved by 2021 [3]. Similarly, well-known corporations such as Lenovo and Haier have used digital technology to improve energy efficiency, implement environmental protection plans, and achieve high-quality economic and environmental development [4]. However, according to the Deloitte Industry 4.0 Investment Survey 2018, 76% of questioned organizations utilize sensors to collect data, but only 33% use big data technology to evaluate the acquired data [5]. Thus, enterprises are still not effectively utilizing the data they acquire, resulting in inadequate digital applications and lower energy efficiency for green innovation [6]. Moreover, as application barriers to digital technology remain high, many corporate managers remain suspicious about the usefulness of digitalization. To address these issues, enterprises may choose more radical technological integration to leverage abundant resources to achieve digitalization; however, they can also improve the efficiency of data application value through digital optimization.

In recent years, researchers have begun to examine the effect of digital technologies on corporate green innovation performance, focusing on two main issues: (1) whether and how digital technology can provide opportunities for green innovation within organizations [7,8]; (2) how digital technology has a greening impact on businesses within industry chains, supply chains, and innovation ecosystems [9–11]. However, existing research is limited by the following shortcomings. First, the majority of studies focus on whether new technologies affect the innovation process [12], rather than considering the impact of optimizing digital technology on the output of GTI. Second, prior research on green innovation in business has primarily focused on external driving factors, such as technology push and market pull [13,14], with few studies examining the impact of enterprise digitalization on green innovation activities by simultaneously including environmental and economic goals as internal drivers. Third, the majority of studies adopt case studies to analyze the relationship between digital technology and firms' GTI [15]; however, few incorporate knowledge management or related theoretical perspectives to quantify this process, which remains difficult to discuss in a systematic and comprehensive way. Therefore, quantitative and mechanistic investigations are required into the impact of digitalization on GTI.

In this study, we focus on how manufacturing enterprises achieve GTI through digital optimization. Two specific questions are posed. (1) What is the mediating effect between digital optimization and GTI? (2) What factors moderate this process? To address these two questions, we employ panel data of listed Chinese manufacturing companies to conduct an empirical study from 2013 to 2019. The contributions of this study are as follows: first, we investigate the transmission and application characteristics of digital information from the perspective of corporate strategy, then take digital optimization as the starting point to explore its impact on enterprise GTI. Second, we examine the mechanism of green R&D collaboration between digital optimization and GTI based on knowledge management theory and empirically test how and to what extent green R&D collaboration mediates this process. Third, based on the optimal distinction theory, we explore the moderating role of external environmental orientation on the relationship between digital optimization and green R&D collaboration. We creatively integrate the dual goals of economic and environmental decision-making by analyzing group coordination and strategy with the external environment, then analyze the influence of enterprise decision-making objectives to improve digital construction and promote green innovation development in accordance with the enterprise's own resources.

The remainder of this study is structured as follows: Section 2 reviews the literature related to this research; the hypothesis is proposed in Section 3; Section 4 presents the methods, including data sources and their measurement; our empirical analysis of the effect of digital optimization on GTI within manufacturing enterprises is described in Section 5; and the findings and their implications are discussed in Section 6.

2. Literature Review

2.1. Digital Optimization

Digitalization research dates back to studies on information systems from the late 1990s [16]. Most of the literature focuses on inter- or intra-organization technology improvement solutions or the use of a single informatization technology tool (such as Enterprise

Resource Planning) for enterprise automation or digitalization [17]. Nowadays, with the explosion of digital technology, the way data are shared, generated, and communicated with consumers has changed significantly [18]. Considering digital technologies as a standard productivity enhancement tool to improve existing operational processes [19], digital optimization is a solution for companies that do not apply digital technology effectively after adopting digital equipment or whose application efficiency is unknown. That is, digital information resources are not sufficient to create successful productivity; however, converting those resources into usable production outputs may lead to digitalization success. Specifically, digital optimization is characterized by (1) a focus on improving digital technology, (2) optimized utilization of digital technology for customers or organizations, and (3) improving the original business operation process to achieve local optimization in four areas: technology and infrastructure, products and services, organizational structure, and finance and operations.

A key area of research analyzes the impact of digital technologies to enhance innovation performance or environmental performance of firms. For example, Lehrer et al. (2018) argue that the use of digital technologies mitigates the negative effects caused by the uncertainty of innovation itself, boosting innovation outcomes and leading to higher economic performance [20]. However, other studies note that digital technologies do not necessarily improve business outcomes. The stereotyped adoption of another firm's digital technologies may result in increased costs and risks for a firm, thereby lowering their innovation performance [21]. Regarding the relationship between digital technology and the environmental performance of businesses, although digital technology enables businesses to acquire economic benefits, it can also have a negative impact on environmental performance [22]. Overall, research on the issue of digitalization and corporate green innovation is still in its infancy, and few studies have empirically established the impact of digital optimization on GTI. Firms that continuously optimize existing digital technology can efficiently track product design, production, and recycling operations throughout the entire product lifespan, ensuring that processes and products are environmentally sustainable [23]. Additionally, energy companies can accelerate decarbonization by leveraging modern digital technology with low-carbon and clean energy production systems [24]. Therefore, it is vital to examine corporate green innovation through a digital lens.

2.2. Green Technological Innovation

Green technological innovation is defined as innovative products and processes that reduce negative environmental impacts [25]. Oltra and Saint-Jean (2009) define green technologies as "innovations consisting of new or improved processes, practices, systems, and products that contribute to environmental sustainability" [26]. In this study, green technologies include environmentally friendly products, processes, and services, as well as organizational management systems that are sensitive to environmental issues and systemic innovations.

Digital technology has expanded opportunities for green innovation research, with digital optimization providing more professional technical support for corporate GTI. Existing research in the field of green innovation primarily examines the driving factors of green innovation from an external perspective, such as environmental regulations [27], tax policies [13], and financial subsidies [28]. With the advent of the digital age, previous green innovation research based on technology-driven, policy-driven, and market-pull factors urgently requires theoretical breakthroughs. Recently, Muhammad et al. (2021) proposed that big data analytics could represent a roadmap toward green innovation [29], and Cao et al. (2021) suggested that digital finance impacts both GTI and energy-environmental performance [30]; thus, digitalization has been increasingly applied in environmental production and process innovation.

2.3. Green R&D Collaboration

R&D collaboration is defined as a partnership formed by businesses to prevent risks, accelerate product development cycles, respond to emergency threats, and reduce transaction costs in the face of high R&D expenditure and unpredictability [31]. Green R&D collaboration is a collaborative process among R&D team members that addresses environmental issues. In terms of corporate R&D investment and outcomes, the widespread use of digital technologies can have a profound impact on intra-organizational communication within local firms and inter-organizational collaboration among multinational groups [32]. Scholars have also reported the related processes and impacts from the perspective of exploratory and exploitative innovation performance, low-carbon and green innovation performance, and open innovation performance [33,34]. Although such research has confirmed the link between R&D collaboration in digital technologies and innovation outcomes, the impact of digital optimization on GTI has not been empirically investigated via green R&D collaboration. Therefore, it is vital to study the role of green R&D collaboration as a bridge between digital optimization and GTI.

2.4. External Environmental Orientation

Environmental orientation refers to a company's attempts to reduce or eliminate the detrimental influence of its commercial activities on the natural environment, and can be classified as internal or external environmental orientation [35]. Given that enterprises must achieve higher environmental goals while meeting the environmental limits imposed by related regulations or policies, external environmental orientation has a greater direct impact on firms. According to the narrow Porter hypothesis [36], environmental regulations will cause businesses to rethink their product design and manufacturing processes, reorient their environmental concerns, and reallocate digital resources to address environmental issues. However, external institutional restraints reinforce a company's collaborative engagement with green R&D, improve product and process design to fulfill environmental needs, and ultimately influence green innovation activities in the direction of a firm's digital optimization. Hence, external environmental orientation may influence digital optimization to promote green R&D collaboration.

Existing studies focus either on the impact of environmental pressures or digital technology on GTI, but ignore the issues of how firms can make balanced decisions to achieve rational allocation of innovation resources under environmental pressures and digital technology situations. Within the context of "carbon neutrality", digitalization and the environment management are particularly important for promoting GTI. Moreover, examining the channels that can transmit this impact will provide key guidance for green innovation decisions. Therefore, evaluating the effect of the digital optimization of manufacturing companies on the performance of GTI represents a significant area of future research.

3. Hypotheses

3.1. Digital Optimization and Green R&D Collaboration

Digital optimization contributes significantly to green R&D collaboration. First, digital optimization directly improves green R&D collaboration among businesses by increasing the information exchange capability of the enterprise and offering a large communication space. Improving digital optimization will promote both the external technology and internal resources of the enterprise, which can expand its original capacity of sending, receiving, and processing information without increasing the cost of additional equipment [37]. This will enlarge the communication space and capacity of information exchange as well as fundamentally broaden the scope of green R&D collaboration. Second, digital optimization improves digital value through the technical information communication capacity of R&D personnel, strengthens the efficiency of information application, and directly accelerates the green R&D collaboration process. As the core of digital information acquisition, transformation, and utilization, R&D members acquire more precise and complete information knowledge through digital optimization, establishing a vast and effective collaborative communication system [38]. This implies that members of the R&D team can collaborate and communicate with other teams both internally and externally under digital optimization. This accelerates the pace of information exchange on green technologies, broadens information exchange routes, and creates more opportunities for new knowledge acquisition and collaboration, ultimately accelerating green R&D collaboration. Therefore, we suggest the following hypothesis:

Hypothesis 1. *Digital optimization exhibits a positive relationship with green R&D collaboration.*

3.2. Green R&D Collaboration and Green Technological Innovation

Green R&D collaboration has a non-linear effect on GTI. When a company's team members collaborate infrequently on green R&D projects, the scope of knowledge and information acquisition is limited. Low-level green R&D collaboration indicates that practitioners lack sufficient connections among groups, which are more likely to be late or excessively sensitive to market demand under rapid changes in the external environment, then fail to effectively use the acquired information in green product and process development [39]. In addition, as GTI requires a wide range of knowledge as an innovation resource reserve, a narrow collaboration scope restricts the acquisition of knowledge information, thereby impacting the output of GTI. As a result, enterprise GTI will be restricted when green R&D collaboration is low.

When the degree of green R&D collaboration within a company is moderate, the limited scope of knowledge and information acquisition is compensated by a broader communication space. To meet the growing external demand for green products, companies must have continuous access to information and expertise to establish new sectoral connections, which helps boost the information interoperability and GTI output of enterprises [40]. Further, expanding the scale of green R&D collaboration facilitates the scope of the selected innovation. Collaboration among developers from different sectors can lead to more impactful innovations with disparate ideas [41]. Owing to knowledge spillover effects, developers may better estimate market demand, coordinate their green innovation operations, and expand their exposure to green information through increased collaboration in green R&D. This tacit coordination will make it easier and faster for R&D teams to establish productive and relevant connections, concentrate on making new discoveries, improve internal communication, and provide firms with additional opportunities to generate GTI under limited resources. For example, extensive collaboration has the opportunity to leverage organizational resources to address low-carbon emission issues, develop cleaner product designs, and reduce environmental and energy footprints [42,43]. Thus, a moderate degree of green R&D collaboration can broaden the source of information knowledge, resulting in a significant improvement in GTI.

However, when green R&D collaboration reaches a high level, the greater coordination costs associated with redundant communication led to the wasteful development of green technology. The more involved a group is in green R&D, the more important it is for individual members to keep their initial connections intact, which can be challenging for corporations to manage. Since most GTI initiatives are the outcome of collaboration among different business units and R&D participants [44], enterprises should set their R&D teams' communication strategies to efficiently coordinate their activities. This makes it challenging for enterprises to maintain large-scale coordination systems while creating green innovation projects. In addition, the establishment of new collaborative relationships generates a large amount of expensive and time-consuming ineffective information transfer, which indirectly weakens the outcomes of effective collaborative communication and lowers the quality of acquired information and knowledge [45]. Consequently, more extensive green R&D collaboration may increase intra-company communication costs, generates invalid information and knowledge, disrupts the transfer and application of green knowledge, and finally has a detrimental effect on GTI.

Hypothesis 2. *Green R&D collaboration exhibits a curvilinear (inverted U-shaped) relationship with corporate GTI.*

3.3. Mediating Effects of Green R&D Collaboration

Green R&D collaboration mediates the relationship between digital optimization and GTI. Innovation has become a collective, collaborative activity that incorporates the knowledge, information, and experience gained by individuals in the organizational learning process [31]. Moreover, digital technology has gradually become a source of information elements for organizational learning and decision-making in R&D projects, whereas the process of digital optimization reinforces the accuracy and reliability of information resources acquisition. As the level of digital optimization increases, a large amount of environmental information and product data regarding manufacturing, R&D, and marketing are generated. It has a cumulative effect on the processing, comprehension, and creative application of relevant knowledge for R&D members [46], thereby promoting green R&D collaborative communication. At that point, how R&D teams perceive and utilize information resources to create inventions is determined not only by the innovators' personal knowledge base but also by the frequency of communication with other members. In particular, R&D members are more effective at filtering out low-quality ideas [47] (Kaplan et al., 2015) and producing more impactful innovations than solo inventors [48]. Such R&D collaboration provides a knowledge base for team members' technical specialization and establishes a relationship between R&D collaboration and innovation performance. As the requirements of GTI knowledge reservation vastly surpass traditional innovation from method and speed, businesses may rely more on enhancing green R&D collaboration through new methods, such as digital optimization, to improve the level of GTI in the digital context [49].

Hypothesis 3. *Green R&D collaboration plays a mediating role in the relationship between digital optimization and corporate GTI.*

3.4. Moderating the Effect of External Environmental Orientation

External environmental orientation amplifies the influence of digital optimization on green R&D collaboration. Specifically, external environment orientation helps enhance green R&D collaboration by raising environmental protection awareness among R&D members and targeting the company's environmental issues by introducing digital optimization techniques. Under sustainable development circumstances, external environmental orientation fosters corporate members to develop ecological responsibility [50]. This awareness has shifted the focus of R&D members from economic benefits to environmental benefits, adjusting the allocation of environmental and innovation resources and accelerating the effectiveness of digital technology in environmental issues. Moreover, environmental orientation assists partners in determining the direction of their environmental cooperation and creates necessary green R&D activities. Since complex GTI requires a certain knowledge base and complex capabilities [51], these knowledge and capability requirements affect not only the organization's internal resource allocation, but also the cooperation's goals with upstream and downstream enterprises. Concurrently, by integrating digital optimization behaviors, the resulting high-quality digital resources help reduce collaboration uncertainty and increase the efficiency of organizational responses [52]. Thus, external environmental orientation could enhance digital optimization and information exchange to collaborate with upstream and downstream industries in green R&D collaboration.

Undeniably, a complex external environment orientation may increase a company's search and coordination expenditures. Although external environmental orientation increases the extent of knowledge search and cost of green R&D collaboration, it also increases the level of "noise" associated with accessing knowledge and information [53,54]. This information noise can impede strategic corporate environmental goals and make it difficult to process redundant data [55,56], thereby partially inhibiting the potential effects of digital optimization on green R&D collaboration [57]. Due to the nature of digital interconnection, researchers and developers from different organizations tend to generate ideas about environmental needs, which prompts R&D personnel to actively engage in environmental issues and generate additional opportunities for innovation [58]. That is, even if external environmental orientation has contained negative impact, its positive effects on green R&D collaboration overwhelm the negative ones. Therefore, in most cases, external environmental orientation positively contributes to digital optimization and green R&D collaboration. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 4. *External environmental orientation positively moderates the relationship between digital optimization and green R&D collaboration.*

4. Methods and Data

4.1. Data and Sampling

In this study, we used the cataloged National Economy Industrial List of the National Bureau of Statistics of the People's Republic of China (2017) to select manufacturing enterprises by industry category. The research sample included listed manufacturing companies in China's Shanghai and Shenzhen A-shares from 2013 to 2019. Further, we excluded enterprises designated as special treatment and specific transfer because these firms exhibit unusual financial performance. Data on firm size, firm age, firm leverage ratio, and total asset turnover were gathered from the RESSET Database and CSMAR Database, which contain basic information of the relevant firms. In addition, as China's Informatization and Networking Plan was originally suggested in 2007 and almost finished in 2012, we expect all listed enterprises to have adopted digital optimization by 2013 and achieved successful digital development by 2019. The resulting data sample contains 11,249 samples from 2237 manufacturing firms. All continuous variables in this study were subjected to upper- and lower-tailed 1% tests. Data analysis was performed using Stata14 software.

4.2. Variables

4.2.1. Dependent Variable

Green technological innovation: Since patents can retain significant information for an extended period, scholars consider patents as a suitable sample for assessing innovation features [13,59,60]. According to Costantini et al. (2015), most international assessments of GTI use the OECD Env-Tech classification list [61]. Therefore, we referred to the OECD Env-Tech list to classify the relevant International Patent Classification and Cooperative Patent Classification and screen the green patents of listed companies in the Chinese manufacturing industry. In this sample, following the contributions of Costantini (2017) and Noailly (2010), GTI was measured by the number of entries in patent databases according to the OECD Env-Tech (2016) list [13,62].

4.2.2. Independent Variable

Digital optimization: Existing research on enterprise digitalization has primarily focused on capital and equipment investments; however, this blinds firms to digital practices because of the inability to observe technological attributes [63]. As most companies are already aware of the importance of digitalization but may be confused about what path to choose to improve corporate performance, we introduced digital optimization behaviors to examine the level of corporate digitalization practices, then conducted content analysis using textual information from annual reports of listed manufacturing companies. According to Xie et al. (2019), content analysis is accomplished by coding relevant expression content and keywords from annual reports of publicly traded manufacturing businesses [64]. The specific analysis was as follows: First, two coders independently screened 100 reports for relevant keywords then cross-checked them against the literature content to determine the final search content. The initial screening should include digital terms such as "digital", "smart", "intelligent", "connected", "IoT", "network", and "information", as well as other fundamental terms associated with digitalization. Second, the statement should incorporate the terms "optimization", "integration", "lean", and "fine", as well as other terms indicating an optimization goal. Finally, according to digital optimization, the key phrases to search should be refined in four areas: technology and infrastructure, products and services, organizational structure, and finance and operations. During the evaluation, we eliminated any content that was not directly related to digital optimization in the production process, such as "information" and certain ambiguous language. Since the purpose of this study was not to determine the frequency of words but rather the extent to which enterprises invest in digital optimization, only duplicate items were removed from the statistics, and the number of items without duplication was taken as the result of enterprise digital optimization.

4.2.3. Moderator

External environmental orientation: As the definition of external environmental orientation focuses on firms that need to comply with environmental constraints imposed by external institutional rules [65], these firms pursue higher environmental goals based on their own needs; thus, external environmental orientation has a more fundamental and direct effect on firms. Based on previous studies [66,67], we employed content analysis to extract pertinent issues from corporate annual reports and social responsibility reports, which included "reducing environmental impact in sales and operations", "environmental monitoring", "purchasing clean technologies/equipment", "responsible waste and residue disposal (separation and treatment)", "process design centered on reducing energy and natural resource consumption in operations", "production planning focused on waste reduction and optimization", "information to customers and organizations about environmental management", "government requirements", "environmental criteria in supplier selection", "contamination and hazardous material/component replacement", and "emission filtration and end-of-pipe control." By recording and organizing the company's compliance with these 11 items and counting them without duplication, we calculated the company's external environmental orientation outcomes.

4.2.4. Mediator

Green R&D collaboration: Numerous studies have assessed the depth of collaboration among supply chain members [31] and the degree of knowledge collaboration [68]. Given that green R&D collaboration is a behavioral observation of the information distribution process, we depicted green R&D collaboration as a combination of team configuration [68] and knowledge networks [69]. To determine which inventors actively pursue green technologies, we leveraged the collaboration of corporate green patent inventors across categories and examined the extent of information sharing among patent inventors.

$$\text{Co-work}_{i,t} = \Sigma_{j\,=\,1}\,(N_{i,j,t}/N_{i,t})^2 \tag{1}$$

where the patent categories correspond to the various technical sectors denoted by j = 1, 2, 3. . . T. Thus, $N_{i,j,t}$ represents the total number of active inventors within firm i, and $N_{j,t}$ is the number of patents assigned to technology category j out of the total number of patents produced by inventors in firm i. Collaboration refers to the ratio of the number of inventors involved in green innovation to the number of patents. Thus, the more developers participate, the more extensive the collaboration.

4.2.5. Controls

To enhance the reliability of the data results, we controlled for the following variables that may affect corporate GTI, including firm size (Size), which is the natural logarithm of total assets at the end of the period; financial leverage (Lev), which is the ratio of total liabilities to total assets at the end of the period; return on total assets (ROA), which is the ratio of net profit to average total assets; proportion of independent directors (Identi), which is the number of independent directors as a percentage of board members; age of the firm (Age); and nature of firm ownership (Pattern), i.e., state-owned firms are marked as 1 and non-state-owned firms are marked as 0. Industry and year dummy variables were also included. Table 1 lists the control variables used in this study.

Table 1. Variables and measurements.

Variable names	Measurements	Data sources	Sources
Green technological innovation	OECD Env-Tech categories	Patentics Database	[13]
Digital optimization	Context analysis	Firms' Annual Reports	[19]
Green R&D collaboration	IPC-CPC categories with Economic Industry	Patentics Database	[70]
External environmental orientation	Context analysis	Firms' Annual Reports	[66]
Firm size	Total assets (billion)	CSMAR Database	[64]
Firm leverage ratio	Total Debt divide Total Capital	CSMAR Database	[71]
Total assets turnover	The ratio of main business income to total assets	CSMAR Database	[64]
Proportion of independent directors	independent directors divide total directors	Resset Database	[72]
Firm age	Number of years listed in the Chinese stock market to year 2013	Resset Database	[64]
Firm Pattern	Stated owned or non-Stated owned	Resset Database	[64]

Table 2 summarizes the data statistics and correlations. Variance inflation factor tests suggest that the maximum value of all variables is 6.7, which is less than 10; thus, no multicollinearity is deemed to have arisen. Table 3 lists the data correlations.

Table 2. Summary statistics.

Variable Types	Variable Names	Variable Symbols	Observation	Mean	Std	Min	Max
Dependent Variable	Green technological innovation	GreenInno	11,249	1.524	13.870	0.000	176.000
Independent Variable	Digital optimization	DIG	10,027	4.540	5.141	0.000	16.000
Controls	Firm size	Size	11,249	21.668	1.115	16.592	26.751
	Firm leverage ratio	Lev	11,249	0.321	0.238	−0.006	10.878
	Total assets turnover	ROA	11,249	0.043	0.090	−3.911	0.863
	Proportion of independent directors	Identi	11,247	0.376	0.056	0.200	0.800
	Firm age	Age	11,249	20.632	5.292	5.000	62.000
	Firm Pattern	Pattern	11,249	0.671	0.142	0.000	1.000
Mediator	Green R&D collaboration	Co-work	11,249	8.924	2.581	0.000	10.000
Moderator	External environmental orientation	EPW	11,219	4.439	2.038	1.000	11.000

Table 3. Correlation matrix.

	GreenInno	DIG	Size	Lev	ROA	Identi	Age	Pattern	EPW	Co-work
GreenInno	1									
DIG	0.022 **	1								
Size	0.197 ***	0.085 ***	1							
Lev	0.086 ***	0.011	0.295 ***	1						
ROA	0.009	−0.015	−0.063 ***	−0.293 ***	1					
Identi	0.001	0.026 ***	−0.011	−0.003	−0.005	1				
Age	0.024 **	−0.052 ***	0.133 ***	0.097 ***	−0.032 ***	−0.043 ***	1			
Pattern	−0.055 ***	0.005	−0.314 ***	−0.171 ***	0.093 ***	0.017 *	−0.233 **	1		
EPW	0.031 ***	0.006	0.332 ***	0.130 ***	−0.021 **	−0.062 ***	0.107 ***	−0.120 **	1	
Co-work	−0.079 ***	−0.048 ***	−0.105 ***	−0.094 ***	−0.021 **	0.034 ***	0.032 ***	0.032 ***	−0.068 ***	1

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

4.3. Method of Estimation

Considering the non-negative, discrete characteristics of such patent data, scholars have argued that simple ordinary least square regression is no longer suitable for regressions, and that Poisson regression models and negative binomial regression models are more appropriate for econometric analysis of such variables [73]. Likelihood-ratio test results indicated that the negative binomial regression model is inapplicable when $a = 0$. In addition, using the pseudo-maximum likelihood technique, Poisson fixed-effect estimation controls for unobservable heterogeneity, zero value, and overdispersion issues [74]. To test our hypotheses, we examined the relationship between digital optimization and GTI through the mediating effect of green R&D collaboration by controlling for firm-level variables. First, we evaluated the model specified below for the full sample:

$$\text{Co-work}_{i,t} = \beta_0 + \beta_1 \text{DIG}_{i,t} + \beta_2 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t} \quad (2)$$

$$\text{Greeninno}_{i,t} = \beta_0 + \beta_1 \text{Co-work}_{i,t} + \beta_2 \text{Co-work}^2{}_{i,t} + \beta_3 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t} \quad (3)$$

$$\text{Greeninno}_{i,t} = \beta_0 + \beta_1 \text{DIG}_{i,t} + \beta_2 \text{DIG}^2{}_{i,t} + \beta_3 \text{Co-work}_{i,t} + \beta_4 \text{Co-work}^2{}_{i,t} + \beta_5 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t} \quad (4)$$

where GreenInno represents GTI performance, DIG is an abbreviation of digital optimization, Co-work refers to green R&D collaboration, and Controls denotes the control variables. Additionally, i, j, and t indicate the firm, industry, and year fixed, respectively.

$$\text{Greeninno}_{i,t} = \beta_0 + \beta_1 \text{DIG}_{i,t} + \beta_2 \text{EPW}_{i,t} + \beta_3 \text{DIG}_{i,t} \times \text{EPW}_{i,t} + \beta_4 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t} \quad (5)$$

$$\begin{aligned}\text{Greeninno}_{i,t} = \beta_0 + \beta_1 \text{DIG}_{i,t} + \beta_2 \text{DIG}^2{}_{i,t} + \beta_3 \text{EPW}_{i,t} + \beta_4 \text{DIG}_{i,t} \times \text{EPW}_{i,t} + \beta_5 \text{DIG}^2{}_{i,t} \times \text{EPW}_{i,t} \\ + \beta_6 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t}\end{aligned} \quad (6)$$

$$\begin{aligned}\text{Greeninno}_{i,t} = \beta_0 + \beta_1 \text{DIG}_{i,t} + \beta_2 \text{DIG}^2{}_{i,t} + \beta_3 \text{Co-work}_{i,t} + \beta_4 \text{Co-work}^2{}_{i,t} + \beta_5 \text{EPW}_{i,t} + \beta_6 \text{DIG}_{i,t} \times \text{EPW}_{i,t} \\ + \beta_7 \text{DIG}^2{}_{i,t} \times \text{EPW}_{i,t} + \beta_8 \text{Controls}_{i,t} + \lambda_t + \tau_j + \varepsilon_{i,t}\end{aligned} \quad (7)$$

where EPW stands for external environmental orientation, and DIG × EPW denotes the moderating effect of digital optimization and external environmental orientation. Moreover, to exclude endogenous factors, the regression variables in this study were lagged by two periods. The theoretical model of this study is shown in Figure 1.

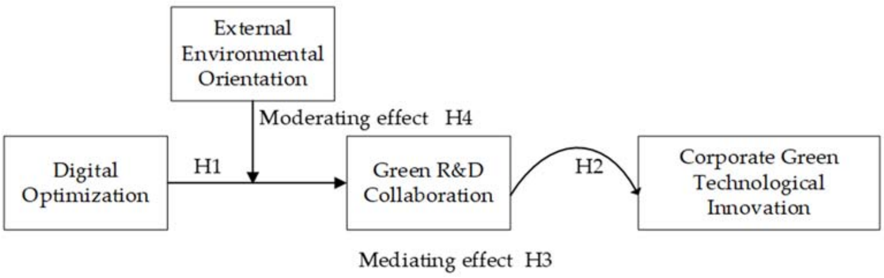

Figure 1. Theoretical model.

5. Results

5.1. Basic Regression and Mediating Effect

Table 4 shows the mediating role of green R&D collaboration between digital optimization and GTI. The regression coefficient for Model 1 was significantly positive and passed the 5% significance test ($\beta = 0.013$, $p < 0.1$), indicating that digital optimization facilitates green R&D collaboration, whereas the quadratic term for Model 2 was not significant ($\beta = -0.002$, ns), indicating that digital optimization has a linear effect on green R&D collaboration. This can be interpreted as a direct effect of digital optimization on green R&D collaboration, which supports Hypothesis 1. Models 3 and 4 shown the results for the relationship between green R&D collaboration and GTI. The results of Model 4 indicate that the primary regression coefficient for green R&D collaboration was significantly positive

($\beta = 0.672$, $p < 0.01$), whereas the secondary regression coefficient was significantly negative ($\beta = -0.076$, $p < 0.01$), indicating that green R&D collaboration has an inverted U-shaped relationship with corporate GTI, which supports Hypothesis 2. This finding suggests that R&D teams with prior experience in green patenting are more likely to generate environmentally friendly inventions. Thus, although green R&D collaboration can help generate GTI to some extent, excessive cross-border collaboration has negative consequences [75].

Table 4. The direct effects of green R&D collaboration.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Co-work	Co-work	GreenInno	GreenInno	GreenInno	GreenInno
DIG	0.013 *	0.046 *			0.067 *	0.071 **
	(0.008)	(0.023)			(0.035)	(0.034)
DIG^2		−0.002			−0.005 **	−0.007 ***
		(0.002)			(0.002)	(0.002)
Co-work			0.136 ***	0.672 ***	−0.108 ***	0.711 ***
			(0.016)	(0.053)	(0.021)	(0.081)
$Co\text{-}work^2$				−0.076 ***		−0.076 ***
				(0.005)		(0.006)
Size	0.919 ***	0.990 ***	0.978 ***	0.954 ***	0.957 ***	0.962 ***
	(0.051)	(0.061)	(0.057)	(0.054)	(0.051)	(0.049)
Lev	1.180 ***	1.486 ***	1.482 ***	1.435 ***	1.450 ***	1.138 ***
	(0.132)	(0.157)	(0.155)	(0.156)	(0.157)	(0.166)
ROA	4.421 ***	6.425 ***	6.459 ***	6.058 ***	6.193 ***	6.154 ***
	(0.730)	(0.957)	(0.947)	(0.907)	(0.910)	(0.922)
Identi	−1.827	−3.135 **	−3.121 **	−2.894 **	−2.962 **	−2.978 **
	(1.167)	(1.489)	(1.484)	(1.428)	(1.355)	(1.364)
Age	−0.010	−0.013	−0.013	−0.017	−0.015	−0.016
	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.012)
Pattern	0.027	0.021	0.030	−0.001	0.006	0.009
	(0.092)	(0.126)	(0.128)	(0.126)	(0.126)	(0.131)
Constant	−3.882 ***	−3.864 ***	−18.476 ***	−19.381 ***	−19.689 ***	−21.287 ***
	(0.821)	(0.821)	(1.436)	(1.524)	(1.670)	(1.662)
Year Fixed	Y	Y	Y	Y	Y	Y
Industry Fixed	Y	Y	Y	Y	Y	Y
Observations	5875	5875	11,247	11,247	5875	5875
Log-likelihood	−3041.71	−3039.97	−23,597.47	−19,712.41	−13,970.54	−11,709.42
Wald chi^2	100.44	108.83	440.18	1976.25	404.86	1252.79
Pseudo R^2	0.0593	0.0599	0.5578	0.6306	0.6107	0.6737

Robust clustered standard errors in parentheses. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

In contrast to Model 5, Model 6 shows a significantly positive coefficient for the primary term of digital optimization ($\beta = 0.071$, $p < 0.05$), a significantly negative coefficient for the secondary term ($\beta = -0.007$, $p < 0.05$), and a significantly negative coefficient for the secondary term of green R&D collaboration ($\beta = -0.076$, $p < 0.01$). These results indicate that digital optimization has a linear relationship with green R&D collaboration, whereas green R&D collaboration has an inverted U-shaped effect on GTI, which ultimately affects green R&D collaboration as a non-linear mediator, thereby supporting Hypothesis 3. Through collaborative communication among team members, companies that implement digital optimization can apply data to corporate technology innovation and organizational change. Given the flexibility of collaborative communication, it is necessary for organizations to re-evaluate their data management strategies and operations to stimulate greater employee creativity and generate more patents that cross technology boundaries.

5.2. Moderating Effect

External environmental orientation has a moderating effect on the relationship between digital optimization and green R&D collaboration, as shown by Model 1 (Table 5), where the coefficient of the primary term of digital optimization was significantly positive ($\beta = 0.041$, $p < 0.05$), indicating that external environmental orientation contributes positively to this relationship, which supports Hypothesis 4. To further validate the relationship between external environmental orientation in digital optimization and GTI, we expanded the moderating effect model to increase the completeness of the theory. According to a combination of Models 2 and 3 (Table 5), the primary term of digital optimization was significantly positive (β = 0.069, $p < 0.05$), whereas the secondary term was significantly negative (β = −0.006, $p < 0.05$), which indicates that digital optimization has an inverted U-shaped effect on the GTI of enterprises. This upward then downward curve can be explained by cost–benefit duality, which states that there are two competing paths (benefit and cost) for a firm's ability to innovate and survive. Managers obtain greater flexibility, responsiveness, and customization in investment, marketing, and production based on multiple data sources, which provides greater space for performance improvement in green product design. However, once the application of digital information reaches a certain threshold, over-reliance on digital optimization and a lack of operational control might disturb innovation conditions [76]. Furthermore, mismatches in operator skill sets, team organization, and newer technology requirements will limit innovation flexibility, which further exhibit "diminishing utility" and higher internal transaction costs on digital optimization [77]. Models 4 and 5 were used to evaluate the moderating effect of external environmental orientation (Table 5). Model 5 shows a negative coefficient for the primary term (β = −0.051, $p < 0.05$) and a significantly positive coefficient for the secondary term (β = 0.003, $p < 0.05$). We conclude that external environmental orientation helps companies strengthen their coordination role upstream and downstream via digital optimization and enables them to develop their own green products and process innovation. However, when this external environmental orientation crosses a specific threshold, digital optimization may disturb green innovation R&D objectives and reduce GTI.

Table 5. Moderator effect of external environmental orientation among digital optimization, Green R&D collaboration, and green technological innovation.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Co-work	GreenInno	GreenInno	GreenInno	GreenInno
DIG	0.015 **	0.010 **	0.069 **	0.014 **	0.279 ***
	(0.023)	(0.011)	(0.033)	(0.027)	(0.093)
DIG^2			−0.006 **		−0.020 ***
			(0.002)		(0.007)
EPW	0.024 *			0.005 *	0.063
	(0.047)			(0.062)	(0.053)
DIG × EPW	0.041 **			−0.006 *	−0.051 **
	(0.022)			(0.006)	(0.020)
DIG^2 × EPW					0.003 **
					(0.001)
Constant	−19.615 ***	−20.815 ***	−20.638 ***	−20.677 ***	−20.648 ***
	(1.220)	(1.517)	(1.474)	(1.292)	(1.289)
Controls	Y	Y	Y	Y	Y
Year Fixed	Y	Y	Y	Y	Y
Industry Fixed	Y	Y	Y	Y	Y
Observations	5875	5875	5875	5875	5875
Log-likelihood	−15,114.07	14,622.97	−14,537.49	−14,594.61	−14,379.58
Wald chi^2	459.08	423.93	479.87	562.20	573.72
Pseudo R^2	0.5294	0.5925	0.5949	0.5933	0.5993

Robust clustered standard errors in parentheses. * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

5.3. Advanced Analysis

Although we have verified the non-linear relationship between digital optimization and GTI, it is difficult to examine the stage effects in detail because of the absence of a threshold value. Consequently, we adopted Hansen's (2000) bootstrap approach to determine whether a threshold impact exists [78]. To avoid the sample selection problem associated with imbalanced threshold regression and maintain as many data samples as possible, we used continuous data after 2013 to obtain a total of 3286 valid samples for the panel threshold regression model.

The results of the digital optimization threshold effect test are presented in Table 6, together with the number of thresholds, F-values, p-values, and critical value significance levels determined from the test for all listed manufacturing enterprises between 2013 and 2019. The models all exhibited significant single-threshold effects, and none exhibited significant double-threshold effects. As shown in Table 6, the threshold value for digital optimization was 10.167, and all threshold variables passed the 5% significance level test. Based on the aforementioned research method and Hansen's perspective, we employed a panel threshold data model based on digital optimization subdivision and considered the single-threshold model with digital optimization as follows.

$$\text{Greeninno}_{i,t} = \alpha + \beta_1 \text{DIG}_{i,t} \times \text{I}\,(\text{X} \leq \text{r1}) + \beta_2 \text{DIG}_{i,t} \times \text{I}\,(\text{X} > \text{r1}) + \gamma \text{X}_{i,t} + \beta_3 \text{Controls}_{i,t} + \varepsilon_{i,t} \quad (8)$$

where X is the threshold variable, which includes the control variables in the benchmark model. r1 is the threshold value: when $X \leq r1$, the indicative function $I\,(X \leq r1)$ is set to 1; otherwise, it is set to 0. Similarly, when $X > r1$, $I\,(X > r1)$ is set to 1; otherwise, it is set to 0. DIG $_{i,t}$ denotes the digital optimization index of firm i in period t, which serves as both the core explanatory variable and threshold variable. Controls are control variables affecting the GTI performance of the firm.

Table 6. Threshold's value.

Variable	Thresholds	Thresholds Number	RSS	MES	F	Prob
DIG	Single	10.167	3.26×10^8	9.39×10^8	37.59	0.03
	Double	48.505	3.01×10^8	9.63×10^8	2.81	0.78

According to the results in Table 7, when digital optimization is low (DIG $\leq$ 10.167), it has a positive effect on GTI; when digital optimization is high (DIG > 10.167), it has a significantly negative effect on GTI. The results also demonstrate that the degree of utilization of digital equipment focuses on quality as well as quantity. When the quantity of digital equipment is excessive, the firm will face the situation of having numerous items to manage, which is not an effective way to obtain data value. Consequently, a moderate driving force can help increase GTI.

Table 7. Threshold's regression.

Variable	Poisson-Regression			
	r1 $\leq$ 10.167	**r1 $\leq$ 10.167**	**r1 > 10.167**	**r1 > 10.167**
DIG	0.006 *	0.062 *	−0.047 *	−0.030
	(0.012)	(0.037)	(0.019)	(0.056)
DIG^2		−0.004		−0.001
		(0.003)		(0.003)
Controls	Y	Y	Y	Y
Observations	4619	4619	1225	1225

Robust clustered standard errors in parentheses. * $p < 0.1$.

5.4. Endogeneity

To address the potential endogeneity issue, we adopted the following analysis approach. (1) In terms of causality, the enhanced performance of GTI may persuade managers that the present technology and organizational structures are adequate, creating an incentive to constantly enhance the process. Hwang (2020) and Parrotta et al. (2014) employed the IV-Poisson method to examine reverse causality and used the mean value of digital optimization of other firms in the same region and industry as the focal firm for representation [79,80]. Models 1 and 2 in Table 8 show that the substituted variable of digital optimization in the basic regression was still significant. (2) We utilized the Heckman two-stage approach to address sample selection bias. The Poisson model was initially selected to regress the entire sample and assess the likelihood of digital optimization. The full sample in the first stage included 1597 listed companies that engaged in GTI during the sample period (denoted by a dummy variable assigned a value of 1) and 375 companies that did not engage in GTI (denoted by a dummy variable assigned a value of 0). In the second stage, the inverse Mills ratio calculated in the first stage was added as a control variable to the dummy variable for GTI. According to Models 3 and 4 in Table 8, even after utilizing the two-stage model, the findings of first-stage were still significant. (3) Models 5 and 6 show the regression results after including the omitted variables of environmental uncertainty [69], intellectual property protection intensity [81], and resource redundancy [82], which revealed that the main regression was still significant after including these three variables.

Table 8. Endogeneity check.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Co-work	Greeninno	Co-work	Greeninno	Co-work	Greeninno
DIG_IV	0.169 **	0.287 *	0.275 *	0.347 **	0.065 *	0.065 *
	(0.027)	(0.043)	(0.056)	(0.039)	(0.032)	(0.032)
DIG^2_IV		−0.035 **		−0.020 *		−0.006 *
		(0.004)		(0.003)		(0.003)
Intellectual property					3.577 *	3.462
					(0.087)	(0.076)
Resource redundancy					0.283	0.336
					(0.008)	(0.011)
Environmental uncertainty					1.035	1.079
					(0.022)	(0.024)
Controls	Y	Y	Y	Y	Y	Y
Year Fixed	Y	Y	Y	Y	Y	Y
Industry Fixed	Y	Y	Y	Y	Y	Y
Observations	10025	5875	10025	5875	10025	5875
LM	126.392	115.637				
	[0.000]	[0.000]				
Log-likelihood	−7179.44	−5836.81	−6859.24	−7669.05	−19365.73	−21,447.60
Wald chi^2	125.67	118.29	309.45	293.59	373.54	335.86
PseudoR^2	0.248	0.227	0.444	0.415	0.471	0.422

Robust clustered standard errors in parentheses. *p*-values in square brackets. * $p < 0.1$. ** $p < 0.05$.

5.5. Robustness

Table 9 illustrates the robustness test used to examine the relationship between digital optimization and GTI. The results indicate that the regression results were robust when (1) explanatory variables were re-measured in Model 1, (2) firms without GTI were excluded from Model 2, (3) alternative regression models (negative binomial) were applied in Model 3, (4) first-order lagging was applied in Model 4, and (5) non-linear cubic terms were analyzed in Model 5.

Table 9. Robustness check.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
DIG	0.041 **	0.063 **	0.068 *	0.036	0.091
	(0.011)	(0.030)	(0.026)	(0.040)	(0.077)
DIG^2	−0.003 **	−0.005 **	−0.004 *	−0.002	−0.010
	(0.001)	(0.002)	(0.001)	(0.009)	(0.014)
DIG^3					0.000
					(0.000)
Controls	Y	Y	Y	Y	Y
Year Fixed	Y	Y	Y	Y	Y
Industry Fixed	Y	Y	Y	Y	Y
Pseudo R^2	0.623	0.595	0.470	0.554	0.587
Observations	5427	2990	5908	7728	5875

Robust clustered standard errors in parentheses. * $p < 0.1$. ** $p < 0.05$.

6. Discussion and Conclusions

6.1. Research Conclusions

In this study, we examine the mechanism by which digital optimization impacts the process of corporate GTI, focusing on the mediating role of green R&D collaboration and the moderating role of external environmental orientation. Based on annual report data of listed manufacturing companies from 2013 to 2019, a Poisson fixed panel model was applied to the data. The main findings of this study are as follows

First, we observe a significant positive correlation between digital optimization and corporate green R&D collaboration. Digital optimization provides enterprises with more diverse information resources, as well as more space for R&D collaboration in environmental protection and green innovation. Hence, improvements in digital optimization will enhance green R&D collaboration in enterprises. Second, the relationship between green R&D collaboration and firms' GTI is characterized by an inverted U shape. Although some researchers discovered a linear link between R&D collaboration and firm innovation performance [83], our study demonstrates that green R&D collaboration is not only favorably associated with corporate GTI. That is, green R&D collaboration initially has a significant driving effect on the performance of GTI; however, as a certain threshold is exceeded, the negative effect of coordination costs increases and eventually outweighs the positive driving effect of the collaboration process, resulting in this non-linear characteristic. Third, green R&D collaboration acts as a mediator between digital optimization and a firm's performance in GTI. This suggests that firms' information and knowledge can influence the collaboration characteristics of their R&D teams and affect their GTI. Fourth, external environmental orientation has a positive moderating effect on the relationship between digital optimization and enterprise collaboration on green R&D. External environmental orientation satisfies the environmental legitimacy requirements of businesses and is effective in utilizing digital information to improve environmental performance and boost the level of innovation in green products and processes. Fifth, the threshold effect test between firms' digital optimization and GTI indicates that this non-linear relationship has a critical point. That is, when the scale of digital optimization is less than or greater than 10 items, digital optimization may inhibit GTI on each side. These conclusions remain valid even after the robustness tests.

6.2. Theoretical Implications

First, this study provides a new viewpoint on the relationship between digital optimization and corporate GTI. Previous research has focused on using digital technology and digital transformation to modify corporate resource allocation, including improving innovation performance in terms of perception and access to information. However, this does not provide the amount of digital information that can be used, and green innovation research remains in its infancy. Moreover, existing research on digital optimization is limited to four aspects: technology and infrastructure, products and services, organizational structure, and finance and operations [84], with few studies on the mechanisms by which digital optimization affects GTI. As a result, this study overcomes the limitations of previous studies that investigate the transmission and application characteristics of digital information from the perspective of corporate strategy and enriches the theoretical view of corporate digital optimization as a driver of GTI.

Moreover, by organically combining knowledge management theory, this study presents a research framework of "digital optimization—green R&D collaboration—enterprise GTI", which compensates for the limitations of current "theoretical black box" research on the relationship between digitalization and green innovation. Although previous literature has highlighted the critical role of R&D collaboration in improving innovation performance (e.g., drivers of R&D collaboration, characteristics of R&D collaboration networks), how and to what extent R&D collaboration mediates the process of digitalization and green innovation mechanisms still needs to be empirically tested [84]. In this study, we analyze R&D personnel collaboration at the knowledge management network level, provide an in-depth interpretation of green R&D collaboration between digital optimization and GTI, and clarify firms' acquisition of information through digital technology with a unique theoretical perspective on this internal process. Thus, we establish a more comprehensive model framework for digital optimization and GTI based on knowledge management.

Finally, we examine the impact of the interaction between environmental and economic strategies on corporate GTI activities, which advocates the development of optimal differentiation theory in this context. The majority of extant green innovation studies are based on "weak", "narrow", and "strong" versions of the Porter hypothesis [36], which states that environmental regulations can enhance firms' environmental performance and green innovation. Firms face multiple constraints during their development period, where they need to strike a balance between reallocating resources rapidly enough to respond to peer rivalry and refining their production processes to achieve environmental legitimacy. When the simultaneous requirements of increasing digital construction and enhancing environmental protection increase, organizations will struggle to achieve a multi-strategy balance because of a lack of discussion on the relationship between digital technology and environmental considerations. Here, we examine the balance between economic competitiveness and environmental legitimacy in light of the opposing strategic objectives of competing in the market and achieving environmental requirements. By establishing a direct link between digital optimization, external environmental orientation, and corporate green R&D collaboration, we argue that legitimacy in the eyes of stakeholders can regulate corporate resource allocation when faced with related environmental pressures. This finding also agrees well with the optimal distinctiveness theory, which states that firms should reconcile the competitive demands of consistency and differentiation [85], thereby providing a new perspective on optimal distinctiveness theory.

6.3. Practical Implications

First, with regard to technology management, the digitalization process will continue to face new obstacles in a variety of areas, including cyber security, data access regulation, data protection and privacy, and excessive energy usage, all of which impede green development in organizations. Enterprises can address these challenges by developing infrastructure for energy data sharing, strengthening network data security, allowing or restricting access to data, adjusting their digital technology operations in a timely manner to increase production and business operation efficiency, and providing practical digital operation solutions to improve GTI. In addition, firms can leverage the dissemination of digital information to encourage the sharing of advanced technologies, improve the implementation of low-carbon technologies, and offer strategic assurance for technological advancement.

Second, in terms of team management, enterprises should minimize R&D members' reluctance to use digital technology and boost R&D workgroup communication as much as feasible to maximize GTI output. Specifically, enterprise managers should gradually increase their digital technology awareness by fostering organizational learning and continuously assessing employees' digital literacy, moderately intensifying the green R&D collaboration process, alleviating cognitive constraints and fears related to digital change, and provide cognitive assurance for digital optimization to improve green R&D decisions. Furthermore, manufacturing companies should actively expand cooperation channels and promote cooperation among members by assigning inventors to temporary projects to maintain good, effective, and continuous knowledge sharing between inventors and research institutions.

Third, by enhancing cooperation between digital and environmental plans, businesses should improve their perception of external environmental needs in achieving GTI. Environmental problem-solving may entail complicated internal and external linkages inside the organization [58], and the external environment's demands affect the achievement of the firm's economic goals. To achieve carbon-neutral goals and environmental sustainability, manufacturing companies need to meet environmental demands from a variety of stakeholders, for example, by improving corporate environmental performance and green innovation performance. Therefore, companies should enhance their perception of external environmental requirements, find solutions to environmental problems using data, foster an environment conducive to green technology R&D, and strengthen innovation mechanisms to boost their environmental and innovation competitiveness.

6.4. Limitations and Further Research

This study has two main limitations. First, the diversity of text languages complicates content analysis. The position of text appearance and semantic judgment are more challenging to ascertain because there is no universal representation of digital optimization, which may cause imperfect data statistics and information loss. Therefore, future studies could employ more accurate and diversified statistics from newspapers and reports to confirm these findings. Second, the specific issues of digitalization according to the characteristics of enterprises should be studied in more detail. Since the term "digital" is characterized by cross-organizational or cross-board features, the specific study scope and analytical objectives must be considered when addressing particular concerns. Thus, future studies should be undertaken from the perspective of industrial chains and inter-enterprises to investigate the digital optimization characteristics of manufacturing firms. In the future, digital input analysis can be performed for certain types of industries along with specific investments in digital infrastructure, which will help examine the role of digital optimization in businesses from multiple perspectives.

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References

1. Lin, B.; Bega, F. China's Belt & Road Initiative coal power cooperation: Transitioning toward low-carbon development. *Energy Pol.* **2021**, *156*, 112438. [CrossRef]
2. Rizos, V.; Behrens, A.; Van der Gaast, W.; Hofman, E.; Ioannou, A.; Kafyeke, T.; Flamos, A.; Rinaldi, R.; Papadelis, S.; Hirschnitz-Garbers, M. Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. *Sustainability* **2016**, *8*, 1212. [CrossRef]
3. Wu, S.; Fan, D.; Su, Y. The co-evolution of global legitimation and technology upgrading: The case of Huawei. *Am. Econ. Rev.* **2021**, *24*, 8. [CrossRef]
4. Numminen, S.; Lund, P.D. Frugal energy innovations for developing countries—A framework. *Glob. Chall.* **2017**, *1*, 9–19. [CrossRef] [PubMed]
5. Hanley, T.; Daecher, A.; Cotteleer, M.; Holdowsky, J. The Industry 4.0 Paradox. Available online: https://www2.deloitte.com/content/dam/Deloitte/mx/Documents/energy-resources/2018/Industry-4dot0-Paradox-Overcoming-disconnects-on-the-path-to-digital-transformation.pdf (accessed on 16 June 2018).
6. Xue, L.; Zhang, Q.; Zhang, X.; Li, C. Can digital transformation promote green technology innovation? *Sustainability* **2022**, *14*, 7497. [CrossRef]
7. Moşteanu, N.R.; Faccia, A.; Cavaliere, L.P.L. Digitalization and green economy-changes of business perspectives. In Proceedings of the 2020 4th International Conference on Cloud and Big Data Computing, Virtual, UK, 26–28 August 2020.
8. Wei, Z.; Sun, L. How to leverage manufacturing digitalization for green process innovation: An information processing perspective. *Ind. Manag. Data Syst.* **2021**, *121*, 1026–1044. [CrossRef]

9. Ranta, V.; Aarikka-Stenroos, L.; Väisänen, J.-M. Digital technologies catalyzing business model innovation for circular economy—Multiple case study. *Resour Conserv Recycl* **2021**, *164*, 105155. [CrossRef]
10. Nascimento, D.L.M.; Alencastro, V.; Quelhas, O.L.G.; Caiado, R.G.G.; Garza-Reyes, J.A.; Rocha-Lona, L.; Tortorella, G. Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context. *J. Manuf. Technol. Manag.* **2019**, *30*, 607–627. [CrossRef]
11. Sarkis, J.; Kouhizadeh, M.; Zhu, Q.S. Digitalization and the greening of supply chains. *Ind. Manag. Data Syst.* **2020**, *121*, 65–85. [CrossRef]
12. Trantopoulos, K.; von Krogh, G.; Wallin, M.W.; Woerter, M. External Knowledge and Information Technology: Implications for Process Innovation Performance. *MIS Q.* **2017**, *41*, 287. [CrossRef]
13. Costantini, V.; Crespi, F.; Palma, A. Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Res. Policy* **2017**, *46*, 799–819. [CrossRef]
14. Kemp, R.; Oltra, V. Research insights and challenges on eco-innovation dynamics. *Ind. Innov.* **2011**, *18*, 249–253. [CrossRef]
15. Zheng, J.; Wang, X. Can mobile information communication technologies (ICTs) promote the development of renewables?—Evidence from seven countries. *Energy Pol.* **2021**, *149*, 112041. [CrossRef]
16. Zammuto, R.F.; Griffith, T.L.; Majchrzak, A.; Dougherty, D.J.; Faraj, S. Information technology and the changing fabric of organization. *Organ Sci.* **2007**, *18*, 749–762. [CrossRef]
17. Tarigan, Z.J.H.; Siagian, H.; Jie, F. Impact of enhanced Enterprise Resource Planning (ERP) on firm performance through green supply chain management. *Sustainability* **2021**, *13*, 4358. [CrossRef]
18. Lee, J.; Kao, H.-A.; Yang, S. Service innovation and smart analytics for industry 4.0 and big data environment. *Procedia Cirp* **2014**, *16*, 3–8. [CrossRef]
19. Lozic, J. Core concept of business transformation: From business digitization to business digital transformation. In Proceedings of the 48th International Scientific Conference on Economic and Social Development—"Managerial Issues in Modern Business", Warsaw, Poland, 28–29 November 2019.
20. Lehrer, C.; Wieneke, A.; Vom Brocke, J.; Jung, R.; Seidel, S. How big data analytics enables service innovation: Materiality, affordance, and the individualization of service. *J. Manag. Inform. Syst.* **2018**, *35*, 424–460. [CrossRef]
21. Tallon, P.P.; Ramirez, R.V.; Short, J.E. The Information Artifact in IT Governance: Toward a Theory of Information Governance. *J. Manag. Inform. Syst.* **2013**, *30*, 141–177. [CrossRef]
22. Cardinali, P.G.; De Giovanni, P. Responsible digitalization through digital technologies and green practices. *Corp. Soc. Responsib. Environ. Manag.* **2022**, *29*, 984–995. [CrossRef]
23. De Medeiros, J.F.; Ribeiro, J.L.D.; Cortimiglia, M.N. Success factors for environmentally sustainable product innovation: A systematic literature review. *J. Clean. Prod.* **2014**, *65*, 76–86. [CrossRef]
24. El-Kassar, A.-N.; Singh, S.K. Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technol. Forecast. Soc. Chang.* **2019**, *144*, 483–498. [CrossRef]
25. Fussler, C.; James, P. *Driving Eco-Innovation: A Breakthrough Discipline for Innovation and Sustainability*; Pitman Publishing: Washington, DC, USA, 1996; pp. 23–25.
26. Oltra, V.; Saint Jean, M. Sectoral systems of environmental innovation: An application to the French automotive industry. *Technol. Forecast. Soc. Chang.* **2009**, *76*, 567–583. [CrossRef]
27. Porter, M.; Van der Linde, C. Green and competitive: Ending the stalemate. In *The Dynamics of the Eco-Efficient Economy: Environmental Regulation and Competitive Advantage*; Wubben, E.F.M., Ed.; Edward Elgar Publishing: Cheltenham, UK, 1995; pp. 67–79.
28. Cecere, G.; Corrocher, N.; Mancusi, M.L. Financial constraints and public funding of eco-innovation: Empirical evidence from European SMEs. *Small Bus. Econ.* **2020**, *54*, 285–302. [CrossRef]
29. Waqas, M.; Honggang, X.; Ahmad, N.; Khan, S.A.R.; Iqbal, M. Big data analytics as a roadmap towards green innovation, competitive advantage and environmental performance. *J. Clean. Prod.* **2021**, *323*, 128998. [CrossRef]
30. Cao, S.; Nie, L.; Sun, H.; Sun, W.; Taghizadeh-Hesary, F. Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *J. Clean. Prod.* **2021**, *327*, 129458. [CrossRef]
31. Kobarg, S.; Stumpf-Wollersheim, J.; Welpe, I.M. More is not always better: Effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. *Res. Policy* **2019**, *48*, 1–10. [CrossRef]
32. Scuotto, V.; Santoro, G.; Bresciani, S.; Del Giudice, M. Shifting intra-and inter-organizational innovation processes towards digital business: An empirical analysis of SMEs. *Creat. Innov. Manag.* **2017**, *26*, 247–255. [CrossRef]
33. Un, C.A.; Cuervo-Cazurra, A.; Asakawa, K. R&D collaborations and product innovation. *J. Prod. Innov. Manag.* **2010**, *27*, 673–689. [CrossRef]
34. Maietta, O.W. Determinants of university–firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Res. Policy* **2015**, *44*, 1341–1359. [CrossRef]
35. Banerjee, S.B. Corporate environmentalism: The construct and its measurement. *J. Bus. Res.* **2002**, *55*, 177–191. [CrossRef]
36. Porter, M.E. Competitive advantage, agglomeration economies, and regional policy. *Int. Reg. Sci. Rev* **1996**, *19*, 85–90. [CrossRef]
37. Liu, B.; Yang, B.; Xiao, J.; Zhu, D.; Zhang, B.; Wang, Z.; Dong, M. Review of Optimization Dynamically Applied in the Construction and the Application Potential of ICT. *Sustainability* **2021**, *13*, 5478. [CrossRef]
38. Orellana, S. Digitalizing collaboration. *Res. Technol. Manag.* **2017**, *60*, 12–14. [CrossRef]

39. Adomako, S. Environmental collaboration, sustainable innovation, and small and medium-sized enterprise growth in sub-Saharan Africa: Evidence from Ghana. *Sustain. Dev.* **2020**, *28*, 1609–1619. [CrossRef]
40. Kong, T.; Feng, T.; Ye, C. Advanced manufacturing technologies and green innovation: The role of internal environmental collaboration. *Sustainability* **2016**, *8*, 1056. [CrossRef]
41. Schilling, M.A.; Green, E. Recombinant search and breakthrough idea generation: An analysis of high impact papers in the social sciences. *Res. Policy* **2011**, *40*, 1321–1331. [CrossRef]
42. Vachon, S.; Klassen, R.D. Green project partnership in the supply chain: The case of the package printing industry. *J. Clean. Prod.* **2006**, *14*, 661–671. [CrossRef]
43. Montabon, F.; Sroufe, R.; Narasimhan, R. An examination of corporate reporting, environmental management practices and firm performance. *J. Oper. Manag.* **2007**, *25*, 998–1014. [CrossRef]
44. Günther, W.A.; Rezazade Mehrizi, M.H.; Huysman, M.; Feldberg, F. Debating big data: A literature review on realizing value from big data. *J. Strateg. Inf. Syst.* **2017**, *26*, 191–209. [CrossRef]
45. Yli-Renko, H.; Autio, E.; Sapienza, H.J. Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. *Strateg. Manag. J.* **2001**, *22*, 587–613. [CrossRef]
46. Cohen, W.M.; Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [CrossRef]
47. Kaplan, S.; Vakili, K. The double-edged sword of recombination in breakthrough innovation. *Strateg. Manag. J.* **2015**, *36*, 1435–1457. [CrossRef]
48. Fleming, L. Recombinant uncertainty in technological search. *Manag. Sci.* **2001**, *47*, 117–132. [CrossRef]
49. Wuchty, S.; Jones, B.F.; Uzzi, B. The increasing dominance of teams in production of knowledge. *Science* **2007**, *316*, 1036–1039. [CrossRef]
50. Aboelmaged, M. Direct and indirect effects of eco-innovation, environmental orientation and supplier collaboration on hotel performance: An empirical study. *J. Clean. Prod.* **2018**, *184*, 537–549. [CrossRef]
51. Trajtenberg, M.; Henderson, R.; Jaffe, A. University versus corporate patents: A window on the basicness of invention. *Econ. Innov. New Technol.* **1997**, *5*, 19–50. [CrossRef]
52. Pettus, M.L.; Kor, Y.Y.; Mahoney, J.T. Stepping stones to firm growth: Evidence from the deregulated US railroad industry. *Acad. Manag. Proc.* **2010**, *1*, 1–6. [CrossRef]
53. Drover, W.; Wood, M.S.; Corbett, A.C. Toward a cognitive view of signalling theory: Individual attention and signal set interpretation. *J. Manag. Stud.* **2018**, *55*, 209–231. [CrossRef]
54. Puranam, P.; Singh, H.; Zollo, M. Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Acad. Manag. J.* **2006**, *49*, 263–280. [CrossRef]
55. Chaiken, S.; Trope, Y. *Dual-Process Theories in Social Psychology*; Guilford Press: New York, NY, USA, 1999; pp. 83–86.
56. Evans, J.S.B. Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol.* **2008**, *59*, 255–278. [CrossRef]
57. Appio, F.P.; De Luca, L.M.; Morgan, R.; Martini, A. Patent portfolio diversity and firm profitability: A question of specialization or diversification? *J. Bus. Res.* **2019**, *101*, 255–267. [CrossRef]
58. Aragón-Correa, J.A.; Sharma, S. A Contingent Resource-Based View of Proactive Corporate Environmental Strategy. *Acad. Manag. Rev.* **2003**, *28*, 71–88. [CrossRef]
59. Dechezleprêtre, A.; Glachant, M.; Haščič, I.; Johnstone, N.; Ménière, Y. Invention and Transfer of Climate Change–Mitigation Technologies: A Global Analysis. *Rev. Environ. Econ. Policy* **2011**, *5*, 109–130. [CrossRef]
60. Jaffe, A.B.; Palmer, K. Environmental Regulation and Innovation: A Panel Data Study. *Rev. Econ. Stat.* **1997**, *79*, 610–619. [CrossRef]
61. OECD. Patent Search Strategies for the Identification of Selected Environment-Related Technologies (ENV-TECH). Available online: https://www.oecd.org/environment/consumption-innovation/ENV-tech%20search%20strategies,%20version%20for%20OECDstat%20(2016).pdf (accessed on 29 March 2016).
62. Noailly, J.; Batrakova, S. Stimulating energy-efficient innovations in the Dutch building sector: Empirical evidence from patent counts and policy lessons. *Energy Pol.* **2010**, *38*, 7803–7817. [CrossRef]
63. Park, Y.; Mithas, S. Organized Complexity of Digital Business Strategy: A Configurational Perspective. *MIS Q.* **2020**, *44*, 85–127. [CrossRef]
64. Xie, X.M.; Huo, J.G.; Zou, H.L. Green process innovation, green product innovation, and corporate financial performance: A content analysis method. *J. Bus. Res.* **2019**, *101*, 697–706. [CrossRef]
65. North, D.C. A transaction cost theory of politics. *J. Theor. Polit.* **1990**, *2*, 355–367. [CrossRef]
66. Chan, R.Y.; He, H.; Chan, H.K.; Wang, W.Y. Environmental orientation and corporate performance: The mediation mechanism of green supply chain management and moderating effect of competitive intensity. *Ind. Mark. Manag.* **2012**, *41*, 621–630. [CrossRef]
67. Baker, W.E.; Sinkula, J.M. Market orientation and the new product paradox. *J. Prod. Innov. Manag.* **2005**, *22*, 483–502. [CrossRef]
68. Vakili, K.; Kaplan, S. Organizing for innovation: A contingency view on innovative team configuration. *Strateg. Manag. J.* **2021**, *42*, 1159–1183. [CrossRef]
69. Moreira, S.; Markus, A.; Laursen, K. Knowledge diversity and coordination: The effect of intrafirm inventor task networks on absorption speed. *Strateg. Manag. J.* **2018**, *39*, 2517–2546. [CrossRef]

70. Vedula, S.; York, J.G.; Corbett, A.C. Through the Looking-Glass: The Impact of Regional Institutional Logics and Knowledge Pool Characteristics on Opportunity Recognition and Market Entry. *J. Manag. Stud.* **2019**, *56*, 1414–1451. [CrossRef]
71. Nemlioglu, I.; Mallick, S.K. Do Managerial Practices Matter in Innovation and Firm Performance Relations? New Evidence from the UK. *Eur. Financ. Manag.* **2017**, *23*, 1016–1061. [CrossRef]
72. Armstrong, C.S.; Core, J.E.; Guay, W.R. Do independent directors cause improvements in firm transparency? *J. Financ. Econ.* **2014**, *113*, 383–403. [CrossRef]
73. Shaw, D. On-site samples' regression: Problems of non-negative integers, truncation, and endogenous stratification. *J. Econom.* **1988**, *37*, 211–223. [CrossRef]
74. Silva, J.M.C.S.; Tenreyro, S. The log of gravity. *Rev. Econ. Stat.* **2006**, *88*, 641–658. [CrossRef]
75. Bercovitz, J.; Feldman, M. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Res. Policy* **2011**, *40*, 81–93. [CrossRef]
76. Hanseth, O.; Ciborra, C. *Risk, Complexity and ICT.*; Edward Elgar Publishing: Northampton, MA, USA, 2007; pp. 44–57.
77. Myers, I.B.; Myers, P.B. *Gifts Differing: Understanding Personality Type*, 2nd ed.; Nicholas Brealey: London, UK, 2010; pp. 127–136.
78. Hansen, B.E. Sample splitting and threshold estimation. *Econometrica* **2000**, *68*, 575–603. [CrossRef]
79. Hwang, I. The effect of collaborative innovation on ICT-based technological convergence: A patent-based analysis. *PLoS ONE* **2020**, *15*, e0228616. [CrossRef]
80. Parrotta, P.; Pozzoli, D.; Pytlikova, M. The nexus between labor diversity and firm's innovation. *J. Popul. Econ.* **2014**, *27*, 303–364. [CrossRef]
81. Banerjee, R.; Gupta, K. The effects of environmental sustainability and R&D on corporate risk-taking: International evidence. *Energy Econ.* **2017**, *65*, 1–15. [CrossRef]
82. Yun, L.; Yao, X.; Zhu, W.; Zhang, Z. Evaluating the Effect of Redundant Resources on Corporate Entrepreneurial Performance. *Sustainability* **2022**, *14*, 7101. [CrossRef]
83. Hottenrott, H.; Lopes-Bento, C. R&D partnerships and innovation performance: Can there be too much of a good thing? *J. Prod. Innov. Manag.* **2016**, *33*, 773–794. [CrossRef]
84. Sadollah, A.; Nasir, M.; Geem, Z.W. Sustainability and optimization: From conceptual fundamentals to applications. *Sustainability* **2020**, *12*, 2027. [CrossRef]
85. Deephouse, D.L. To be different, or to be the same? It's a question (and theory) of strategic balance. *Strateg. Manag. J.* **1999**, *20*, 147–166. [CrossRef]