Article

Not peer-reviewed version

Embracing Change: How Enterprise Digital Transformation Drives Green Technology Innovation

Yu Hongjian * and Niu Xucan

Posted Date: 5 January 2024

doi: 10.20944/preprints202401.0438.v1

Keywords: Enterprise digital transformation; Green technology innovation; Dynamic capability theory; Manufacturing industry

Article

Embracing Change: How Enterprise Digital Transformation Drives Green Technology Innovation

Hongjian Yu [1,*] and Xucan Niu [1]

Alibaba Business School, Hangzhou Normal University, Hangzhou, China; niuxucan22@163.com
* Correspondence: yuhj1974@126.com

Abstract: Accelerating the green transformation of the economic development mode and promoting high-quality economic development is an international trend and the general direction. This article utilizes data from manufacturing companies listed on the Shanghai and Shenzhen stock exchanges from 2011 to 2021, based on dynamic capability theory, to explore the impact of enterprise digital transformation on green technological innovation. Furthermore, dynamic capabilities are further subdivided into absorptive capacity, innovative capacity, and adaptive capacity to investigate their mediating role. The research findings demonstrate that enterprise digital transformation has a significant positive impact on green technological innovation. Moreover, enterprise digital transformation positively influences the absorptive capacity, innovative capacity, and adaptive capacity, with these three factors playing a mediating role in the impact of enterprise digital transformation on green technological innovation. The results of the bootstrap test confirm this mediating effect. The conclusions of this study are validated through a series of robustness tests. This research not only provides theoretical support for the impact mechanism of digital transformation on green technological innovation but also offers practical insights for enterprises to achieve sustainable development.

Keywords: enterprise digital transformation; green technology innovation; dynamic capability theory; manufacturing industry

1. Introduction

With the rapid development of digital technology and the increasing global call for sustainable development, enterprise digital transformation and green technological innovation have become crucial topics today. In this digital age, businesses face unprecedented opportunities and challenges. To adapt to the rapidly changing market environment, enterprises need to continuously renew and enhance their capabilities to maintain a competitive advantage (Helfat and Raubitschek, 2018). Enterprise digital transformation involves the application of advanced information technology and digital solutions, which disrupt traditional business models and operational methods, creating new value for customers (Vaska *et al.* 2021). Through digital transformation, enterprises can achieve intelligent production processes, data-driven decision-making, and close collaboration with customers and supply chain partners(Maheshwari, 2019; Verhoef *et al.*, 2021). This not only accelerates business development but also brings broader market opportunities. However, enterprise digital transformation is not merely the application of digital technology and digital platforms; it requires the establishment of dynamic capabilities to adapt to change (Gregory Vial, 2019). Dynamic capabilities are the abilities of an enterprise to identify, integrate resources, and build competitive advantages (Teece *et al.*, 2009). They represent an enterprise's capacity to adapt to environmental changes, learn rapidly, and innovate. In the context of digital transformation, enterprises need to possess agility, innovation, and learning capabilities (Daniel Ellström *et al.*, 2021)to adapt to evolving technologies and market demands. Only with these dynamic capabilities can enterprises effectively integrate and leverage digital technologies to drive innovation and improvement.

At the same time, green technological innovation has become an integral part of enterprise digital transformation. With the increasing prominence of global environmental issues, businesses are increasingly in need of adopting sustainable development strategies to reduce their environmental impact. Green technological innovation encompasses efforts such as green product

design, the use of eco-friendly production equipment, and the adoption of green energy sources, aiming to reduce carbon emissions, promote a circular economy, and improve resource efficiency (Huang *et al.*, 2022). By incorporating digital technology into green innovation, enterprises can achieve sustainable resource utilization and environmental protection (Lee *et al.*, 2022), while also meeting the growing consumer demand for sustainable products and services (Lai *et al.*, 2023).

In this context, manufacturing enterprises play a unique role in driving green technological innovation. As the backbone of the real economy, manufacturing companies are directly involved in resource extraction, product manufacturing, and the supply of consumer goods. However, traditional manufacturing models often come with challenges of high energy consumption, emissions, and resource depletion(Liu *et al.*, 2023), imposing significant pressure on the environment. Faced with the challenges of global environmental crises, manufacturing enterprises urgently need to transform and incorporate sustainable development into their strategic plans. China, as a global manufacturing powerhouse with a diverse range of industries, holds a crucial role in green technological innovation. Chinese manufacturing enterprises face dual pressures and opportunities. On one hand, the Chinese government actively promotes green development and environmental protection, introducing a series of policies and standards to encourage manufacturing companies to adopt green technological innovation. In documents such as the "14th Five-Year Plan" and the "Action Plan for Peak Carbon Emissions by 2030," the Chinese government emphasizes the importance of enhancing the role of enterprises as innovation entities, improving their technological innovation capabilities, and supporting them in undertaking major national green and low-carbon technological projects. On the other hand, the global market's demand for green products and sustainable supply chains is growing (Sarkar *et al.*, 2022), providing vast opportunities for Chinese manufacturing enterprises. Therefore, studying the impact of digital transformation on green technological innovation in Chinese manufacturing companies holds significant practical significance.

In this paper, the dynamic capability theory is adopted as the theoretical foundation to investigate the relationship and mechanism between digital transformation and green technological innovation in the manufacturing sector. The study utilizes data from Chinese manufacturing companies listed on the Shanghai and Shenzhen stock exchanges from 2011 to 2021, combined with the CSMAR Digital Transformation Index database. Starting from the current level of green technological innovation in enterprises, identification and testing are conducted to provide valuable insights for countries aiming to achieve green, low-carbon, and circular development as well as the goals of carbon peak and carbon neutrality.

This paper makes several potential research contributions. Firstly, previous studies have provided a limited exploration of the mechanism of the impact of digital transformation on green technological innovation in enterprises. By applying the dynamic capability theory, this paper investigates the mediating role of absorptive capacity, innovative capacity, and adaptive capacity between digital transformation and green technological innovation, enriching the research on the theoretical transmission mechanism between the two and providing a reference for future studies. Secondly, this paper employs a large balanced panel dataset for empirical analysis, which differs from previous studies that mainly relied on questionnaire surveys to measure dynamic capabilities. This approach enhances the representativeness of the sample and further enriches the research on secondary data of dynamic capabilities. Thirdly, by using the number of citations for green patents as a measure of an enterprise's green technological innovation capability, this paper focuses more on the actual quality of green technological innovation, enriching the research in this area and meeting the demand for high-quality innovation-driven development in the context of the digital economy era.

2. Theoretical Background and Hypotheses

2.1. Enterprise Digital Transformation and Green Technology Innovation

Green technological innovation, also known as environmentally friendly technological innovation, is a collective term for management and technological innovations aimed at

 doi:10.20944/preprints202401.0438.v1

environmental protection. It encompasses innovations in various aspects, including product design, green materials, green processes, green equipment, green recycling and treatment, and green packaging (Aguilera-Caracuel and Ortiz-de-Mandojana, 2013). With sustainable development as its core value, green technological innovation utilizes technological and managerial innovations as driving mechanisms to achieve modern technological innovation through environmental protection and energy conservation (Alder *et al.*, 2012). Through green technological innovation, companies can improve the efficiency of raw material and energy utilization (Braun and Wield, 2007), reduce resource utilization costs, and minimize environmental costs (Omonijo and Yunsheng, 2022), thereby lowering operational expenses and gaining a competitive edge in the market competition(Porter and Linde, 1995). In the development of manufacturing companies, green technological innovation, as a new type of technological innovation that simultaneously considers environmental protection and green economic development(Berrone *et al.*, 2013), plays an increasingly important role.

This study considers the factors influencing green technological innovation in companies, which can be categorized into external factors and internal factors. External factors primarily include the financing environment (Lin and Ma, 2022), economic conditions (Li *et al.*, 2023; Yu *et al.*, 2023), market environment (Cleff and Rennings, 1999), and policy environment (Ren *et al.*, 2021), among others. However, the impact of external factors is holistic rather than specific to individual companies. Therefore, this study chooses to empirically investigate the more heterogeneous internal factors.

Internal factors encompass characteristics specific to the company itself, digital capabilities, information acquisition and sharing capabilities, resource allocation capabilities, among others. For instance, company size is a key internal factor determining technological innovation (Feng and Ma, 2020). Company size represents capital accumulation and serves as the foundation and capability for innovation activities (Stock *et al.*, 2002). This implies that larger companies can provide stable resource inputs for technological innovation. Furthermore, green innovation requires the integration of resource consumption and manufacturing system information, as well as the integration of knowledge across different technological domains both within and outside the company (Cui *et al.*, 2020). The company's information acquisition and sharing capabilities can effectively improve resource allocation efficiency, thereby promoting green technological innovation.

Based on the analysis above, the impact of digital transformation on green technological innovation in companies can be mainly reflected in the following two aspects. On one hand, digital transformation can help companies "reduce costs and increase efficiency," optimize resource utilization, and enhance innovation investment. Technological innovation in companies requires a substantial input of resources (Zhou *et al.*, 2017), including stable human and capital investments. The problem of "market failure" caused by its risk uncertainty and externalities leads to private benefits being smaller than social benefits for companies, reducing their motivation for innovation. Therefore, insufficient innovation drive and weak R&D investment are challenges that hinder technological innovation in companies (Hartono and Kusumawardhani, 2019). Digital transformation in companies can improve their ability to perceive the external environment and acquire different resources (Xue *et al.*, 2022), thereby helping them efficiently integrate and obtain internal and external resources. The emergence of intelligent manufacturing and robotic production can liberate some labor, enabling them to shift to more creative and specialized work, thus improving the efficiency of existing human capital utilization (Demartini *et al.*, 2019). Moreover, digital transformation not only helps companies achieve intelligent operations and cost reduction in organizational management but also enhances efficiency and productivity. Digital transformation enables companies to achieve intelligent operations throughout the entire process, from research and development to production and sales, optimizing products and services in-depth, which is beneficial for reducing operating costs (Agarwal *et al.*, 2010) and alleviating the shortage of R&D innovation funding.

On the other hand, digital transformation can enhance a company's capability to acquire, integrate, and share information, thereby increasing innovation opportunities. Compared to general technological innovation, green innovation related to a company's production and low-carbon management processes requires the integration of resource consumption, environmental impact, and

manufacturing system information, which places higher demands on the company's information-sharing capability (Feng *et al.*, 2022).

Based on the analysis of aggregated massive data, digital transformation can facilitate efficient information flow, intelligent analysis, and feedback (Verhoef *et al.*, 2021), which fully meets the requirements of information-sharing capability in companies. It helps companies improve efficiency and seize innovation opportunities based on the acquired information. Building upon the above analysis, the following hypothesis is proposed:

H1: Digital transformation in companies has a positive impact on green technological innovation.

2.2. The Mediating Role of Dynamic Capabilities

Although existing research has shown that digital transformation in companies has a promoting effect on green technological innovation, the specific mechanisms of its impact have not been fully clarified. The digital technology has driven diverse changes in production, innovation, and business models (Hanelt *et al.*, 2021) further intensifying competition among companies. Enhancing competitiveness remains an important issue for companies. According to the dynamic capabilities theory, companies should generate a new capability by integrating, building, and reconfiguring internal and external resources, enabling them to adapt quickly to the business environment and form their own competitive advantage (Teece, 2007). In the context of digital transformation, data is an important resource for value creation in companies (Verhoef *et al.*, 2021). Digitization brings various capabilities to companies, including leveraging digital technology applications such as cloud computing, big data, and artificial intelligence to enhance their technological advantages, as well as efficient integration, analysis, and integration of acquired data information resources, known as information integration capabilities (Günther *et al.*, 2017). This further promotes the development of a company's dynamic capabilities. By utilizing the dynamic capabilities brought by digital transformation, companies can more flexibly respond to the current economic environment and the incentivized market competition, ensuring that they can seize innovation opportunities and promote technological progress in the digital economy era. Previous research has explored the role of dynamic capabilities in various aspects such as firm innovation performance (Zhou *et al.*, 2017), digital circular business models (Eechoud and Ganzaroli, 2023), and competitive advantage (Ferreira *et al.*, 2020). However, it has not extensively investigated the mechanisms through which dynamic capabilities influence the level of green technological innovation in companies.

Currently, there is no unified standard for classifying dynamic capabilities. This study draws on the research of Wang and Ahmed (2007), ZhaoFeng *et al.* (2016), and others, combined with practical considerations, to divide dynamic capabilities into absorptive capacity, innovation capacity, and adaptability. Absorptive capacity refers to the ability of a company to identify, acquire, and integrate external knowledge, and ultimately transform it into its own innovation advantage (Zahra and George, 2002). Innovation capacity refers to the ability of a company to develop new products or technologies. Adaptability, on the other hand, refers to the ability of a company to flexibly respond to changes in the market environment and optimize its resource allocation (Vogel and Güttel, 2013).

The impact of digital transformation on a company's dynamic capabilities is reflected in several aspects. Firstly, digital transformation helps companies absorb and utilize new knowledge, enhancing their absorptive capacity. In the era of the digital economy, data has become an important production factor, and the information contained in processed data holds immense value for companies (Sagiroglu and Sinanc, 2013). Through digital transformation, companies can establish a learning organization, continuously learn and improve by collecting and analyzing large-scale data, thus facilitating the identification and acquisition of valuable new knowledge. Additionally, digital transformation provides real-time feedback and evaluation mechanisms, enabling companies to timely understand their strengths and weaknesses, thereby enhancing their learning and continuous improvement capabilities.

Secondly, digital transformation can optimize a company's innovation model and enhance its innovation capacity. By leveraging digital technologies and platforms, companies can innovate

products and services more rapidly, implement new business models (Vaska *et al.*, 2021), and expand into new market areas. Through collaboration with other companies, research institutions, and startups, as well as the sharing of resources and knowledge, companies can quickly access new technologies, innovations, and market opportunities (Faria *et al.*, 2010). This open innovation model and collaborative network provide broader development space for a company's innovation capacity.

Lastly, digital transformation drives efficiency improvement and resource optimization in companies, enhancing their adaptability. The application of digital technology enhances a company's market perception, resource integration, and organizational collaboration capabilities (Warner and Wäger, 2019), enabling companies to swiftly perceive the external environment and respond accordingly. Data-driven decision-making also enhances a company's sensitivity to environmental changes and response speed (Provost and Fawcett, 2013), strengthening its adaptability. Through data analysis and insights, companies can gain a more accurate understanding of market demand, customer behavior, and competitive dynamics, thus making more astute decisions.

The enhancement of dynamic capabilities such as absorptive capacity, innovation capability, and adaptability enables companies to quickly identify and adapt to changing market demands and environmental pressures. In green technology innovation, companies need to continuously track and understand new trends and requirements in areas such as environmental protection, sustainable development, and energy efficiency (Su *et al.*, 2022). Companies with strong dynamic capabilities possess agility and flexibility (Zhou *et al.*, 2017), allowing them to promptly adjust their technology research and development direction, product design, and production processes to meet the needs of green technology innovation.

Furthermore, the company's dynamic capabilities are closely related to innovation. Green technology innovation requires companies to have exploratory thinking and innovative abilities (Huang *et al.*, 2022), constantly exploring new technologies and solutions to reduce environmental burdens, improve resource utilization efficiency, and enhance ecological benefits. The company's dynamic capabilities promote green technology innovation by facilitating knowledge sharing within the organization, stimulating employees' creative thinking, and fostering an innovative culture (Liao *et al.*, 2009).

Moreover, green technology innovation demands efficient resource integration, including technology, capital, talent, and market resources. Companies with strong dynamic capabilities proactively seek and integrate relevant resources (Teece, 2007) and apply them in the process of green technology innovation. For example, companies can establish collaborative relationships with suppliers, partners, and research institutions to share technology and knowledge and jointly carry out green technology innovation projects.

Lastly, technological innovation is an ongoing learning and adaptation process. Green technology innovation often involves knowledge and information about new technologies, markets, and regulations (Guo *et al.*, 2018). Companies need to have stronger learning capabilities to timely update and apply new knowledge to maintain competitiveness. A company's dynamic capabilities facilitate the acquisition, transformation, and application of knowledge (Nielsen, 2006), assisting companies in continuous improvement and enhancement of green technology innovation.

Based on the previous analysis, digital transformation of companies can enhance the dynamic capabilities of absorptive capacity, innovation capability, and adaptability. Companies with high dynamic capabilities can facilitate information acquisition and knowledge transformation, strengthen their understanding and cognition of green technology innovation, and convert acquired information into valuable knowledge (Nieves and Haller, 2014). This knowledge can then be applied in the process of green technology innovation, thereby driving innovation occurrence and implementation. Additionally, companies with high dynamic capabilities can establish close collaborative relationships with suppliers, partners, and research institutions, sharing technology and knowledge, and forming collaborative networks and innovation ecosystems. Such companies can share risks, engage in collaborative learning and co-innovation, and accelerate the progress and application of green technology innovation.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

Lastly, company's dynamic capabilities enable organizations to possess flexibility and agility (Teece, 2007), allowing them to timely adjust resource allocation, organizational structure, and business processes to adapt to changing market demands and environmental pressures. This flexibility and agility enable companies to better address uncertainties and risks in green technology innovation, swiftly adjust their technology research and development direction, product design, and production processes to meet the needs of green technology innovation.

In conclusion, dynamic capabilities play an intermediary role in the impact of digital transformation on green technology innovation within companies. Based on the aforementioned analysis, the following hypotheses are proposed:

H2a: Absorptive capacity plays an intermediary role in the impact of digital transformation on green technology innovation within companies.

H2b: Innovation capability plays an intermediary role in the impact of digital transformation on green technology innovation within companies.

H2c: Adaptability plays an intermediary role in the impact of digital transformation on green technology innovation within companies.

The theoretical model of this study is shown in Figure 1.

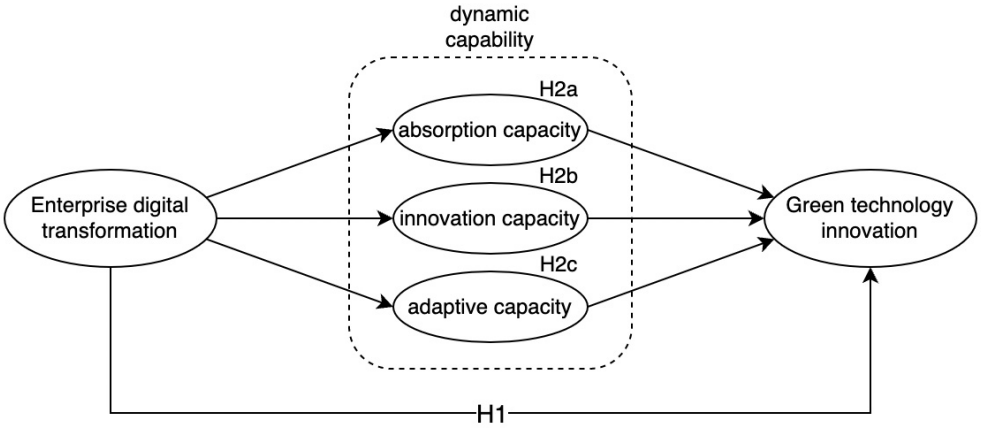

Figure 1. Research model.

3. Research Design

3.1. Sample and Data

To investigate the impact and mechanisms of digital transformation on green technology innovation in companies, this study selected manufacturing companies listed on the Shanghai and Shenzhen stock exchanges between 2011 and 2021 as the initial sample. The reason for selecting manufacturing companies is that this industry generally has high resource consumption and a more urgent demand for green technology innovation. Basic information and financial indicators of the companies were primarily sourced from the CSMAR database, while advertising expenditure data for listed companies was obtained from the WIND financial terminal, and green patent data was sourced from the China Research Data Services Platform (CNRDS). The following criteria were applied to process the sample: (1) Exclusion of sample data with missing information in the panel dataset; (2) Exclusion of observation values from listed companies in abnormal trading states such as ST and *ST. In the end, this study obtained 10,362 observations from 942 listed companies. To mitigate the influence of outliers on the results, the Winsorize method was employed in this study, with a 1% trimming ratio applied to the sample data.

3.2. Variables

3.2.1. Explained Variable

Green technology innovation. Currently, there are two main measurement methods for measuring corporate green technology innovation: questionnaire surveys and patent data from listed companies. In this study, we combined practical considerations and used the International Patent Classification (IPC) codes from the "WIPO Green Inventory" published by the World Intellectual Property Organization (WIPO) to identify green patents of companies and measure their level of green technology innovation accordingly. Since design patents do not utilize IPC classification, this study only considers invention patents and utility model patents as the two types of patents.

Existing approaches for measuring green patents primarily include using the total number of green invention patents and utility model patents as a proxy variable (Yi-ming and Yao, 2022), and using the proportion of the total number of green patents to the total number of patents applied (Song *et al.*, 2022), among others. Although the number of green patent applications by listed companies can effectively depict the output of green technology innovation activities, each patent may have different quality, and a mere count of patent applications cannot adequately represent the true capability of a company's green technology innovation. However, the patent citation is an important indicator of patent technology impact (Guo *et al.*, 2023), and the number of citations received by green patents can better reflect the actual level of a company's green technology innovation. Based on this, this study borrowed the approach of (Guo *et al.* 2023)and used the citation count of a company's green patents to measure its level of green technology innovation. Since the green patent data for 2023 is not yet fully available, this study used the citation count of a company's green patents over the past three years to characterize its level of green technology innovation and subsequently applied a natural logarithm transformation (plus one). Compared to the simple citation count, using a relative measure can eliminate the influence of other unobservable factors, thereby mitigating potential endogeneity issues in the empirical analysis.

3.2.2. Core Explanatory Variable

Digital transformation of enterprises. The mainstream approach for measuring the capability of digital transformation in enterprises is based on the method proposed by Fei *et al.* (2021). Using Python web scraping technology and combining it with annual reports of listed companies, they organized, counted, and aggregated keywords related to big data, artificial intelligence, cloud computing, and other digital technologies to obtain a score representing the capability of digital transformation in enterprises. In this study, we chose to use the data on the Digital Transformation Index of Chinese listed companies from the "Research Database on Digital Transformation of Chinese Listed Companies" jointly published by the CSMAR team and the Department of Business Administration at East China Normal University's School of Business. This database utilizes text scraping and data processing techniques on information disclosed in annual reports, fundraising announcements, qualification certifications, and other relevant announcements of listed companies. It ultimately derives six indicators: strategic leadership, technology driving, organizational empowerment, environmental support, digital achievements, and digital applications. These indicators are weighted to calculate the Digital Transformation Index of enterprises. This index comprehensively analyzes the digital capabilities of listed companies and effectively represents their level of digital transformation.

3.2.3. Intermediate Variable

Dynamic capability. Drawing on the measurement methods proposed by ZhaoFeng *et al.* (2016) and Jichang and Jing (2022), this study uses three variables, namely absorptive capacity, innovative capability, and adaptive capacity, to assess the dynamic capability of enterprises. Absorptive capacity is measured by the ratio of research and development (R&D) expenditure to the total revenue of listed companies in the current year, referred to as Cap_ab. Innovative capability is derived by

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

standardizing the R&D expenditure intensity and the proportion of technical personnel in listed companies and aggregating them, denoted as Cap_in. Adaptive capacity is evaluated by using the coefficient of variation for the three main expenditures of R&D, capital, and advertising, which reflects the flexibility of resource allocation in enterprises. To ensure that the coefficient of variation aligns with the direction of adaptive capacity, the negative value of the coefficient of variation is used to measure the adaptive capacity of enterprises, denoted as Cap_ad. The larger the adjusted coefficient of variation, the stronger the adaptive capacity of the enterprise.

3.2.4. Control Variables

Based on previous research, this study selects key factors that may affect the level of green technology innovation in enterprises as control variables. *Ownership*: Compared to most privately-owned enterprises, state-owned enterprises have stronger financial strength and policy responsiveness, which leads to a greater capacity for green technology innovation. *Age*: The length of time a company has been listed influences its capital accumulation, innovation experience, and overall strength, thereby affecting green technology innovation through the influence of research and development (R&D) investment and innovation efficiency. *Director*: Independent directors play an important role in corporate governance, overseeing and constraining strategic decisions and actions, thus impacting a company's green technology innovation. *Shareholder concentration*: When a few shareholders hold a high proportion of shares, they may prioritize short-term interests over long-term sustainable development, resulting in reduced investment in green technology innovation by the company. *Return on assets (ROA)*: A higher ROA indicates stronger profitability and overall strength of the company, providing the capital for green technology innovation. *Leverage*: A higher leverage ratio indicates a stronger ability of the company to use funds provided by creditors for production and operations, thereby having more funds for green technology innovation. *Growth*: The economic strength of the company directly influences R&D investment. Companies with strong growth have the economic foundation for R&D, and companies with strong profitability have a greater capacity for green technology innovation. *Size*: Company size directly affects R&D investment. Companies with substantial total assets allocate more resources to R&D, resulting in a stronger capacity for green technology innovation in larger enterprises. The main variables are explained in Table 1.

Table 1. Variable definition.

Type	symbol	name	definition
Core explanatory variable	Dig	Enterprise digital transformation	CSMAR database enterprise digital transformation index data
Explained variable	Grepat	Green technology innovation	The number of citations of green patents in 3 years is used to describe the innovation level of green technology of enterprises, and the natural logarithm is taken after adding 1
intermediate variable	Cap_ab	absorption capacity	The ratio of R&D investment to total revenue
	Cap_in	innovation capacity	The value of R&D investment intensity and technical personnel ratio after standardized treatment
	Cap_ad	adaptive capacity	ACV=-σ/mean, where σ is the standard deviation of R&D expenditure intensity, capital expenditure intensity and advertising expenditure intensity, mean is the average of the three expenditure intensity

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

Control variables	Ownership	ownership property	0: non-state-owned enterprise; 1: state-owned enterprise
	Age	listed years	Company listed years = observation year (current statistical deadline) -IPO year
	Director	Proportion of independent directors	The ratio of the number of independent directors to the size of directors
	Shr	ownership concentration	The sum of the shares held by the top five shareholders
	Roa	return on assets	Net profit/average total assets
	Lev	asset-liability ratio	Total liabilities/total assets
	Growth	corporate growth	Revenue growth rate
	Size	firm size	the natural log of the total assets of the firm

3.3. Model Specification

Building upon the theoretical analysis in the previous sections, this study aims to examine whether there is a mediating effect of dynamic capabilities on the relationship between enterprise digital transformation and green technology innovation. To achieve this, the study adopts a mediation effect model for testing. Currently, the commonly used methods for testing mediating effects include the stepwise test, Sobel test, and bootstrap test. While the stepwise test is the most popular method, it has limitations due to its lower statistical power. Therefore, following the mediation effect testing process proposed by WEN and YE (2014), this study establishes the following stepwise regression model.

$$\boldsymbol{Grepat = \beta_0 + \alpha_0 Dig + \sum \alpha_i CON + \varepsilon_i} \quad (1)$$

$$\boldsymbol{Cap_i = \beta_0 + \alpha_0 Dig + \sum \alpha_i CON + \varepsilon_i} \quad (2)$$

$$\boldsymbol{Grepat = \beta_0 + \alpha_0 Dig + \alpha_1 Cap_i + \sum \alpha_i CON + \varepsilon_i} \quad (3)$$

In the equations, $\boldsymbol{\beta_0}$ represents the model's intercept, CON denotes the selected control variables, and $\boldsymbol{\varepsilon_i}$ stands for the random disturbance term. Formula (1) serves as the baseline regression model, employed to examine the impact of corporate digital transformation on green technological innovation, thereby testing hypothesis H1. Formula (2) is utilized to assess whether corporate digital transformation affects dynamic capabilities. Formula (3) is employed to examine whether corporate digital transformation influences green technological innovation through its impact on dynamic capabilities, thereby testing hypotheses H2a, H2b, and H2c.

4. Empirical Testing

4.1. Descriptive Statistics

The descriptive statistics of the main variables are presented in the Table 2. The maximum value of Green Technology Innovation (Grepat) is 6.997, while the minimum value is 0, indicating significant differences among listed companies in terms of green technology innovation. The average value of the Enterprise Digital Transformation Index is 36.65, with a maximum value of 64.14, highlighting substantial variations in the level of digital transformation among listed companies. Only a small number of companies have achieved an advanced level of digitalization, while the majority are still in the early stages of transformation, indicating relatively weak digital capabilities. Furthermore, there is considerable disparity in innovation capability among listed companies, as

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

evidenced by a standard deviation of 1.373, particularly in comparison to absorptive capacity and adaptive capacity. In conclusion, the weak innovation capability of certain sample companies may be a crucial factor influencing green technology innovation. The descriptive statistics of each variable align closely with existing research findings.

Table 2. Descriptive statistics.

Variable	N	Mean	p50	SD	Min	Max
grepat	10362	1.399	0	1.992	0	6.997
dti	10362	36.65	33.99	10.36	23.44	64.14
Cap_ab	10362	0.0600	0.0370	0.109	0.00100	0.921
Cap_in	10362	0	-0.0740	1.373	-3.166	3.527
Cap_ad	10362	-0.692	-0.602	0.364	-2.201	-0.217
ownership	10362	0.304	0	0.460	0	1
age	10362	11.29	10	6.860	0	31
director	10362	37.50	33.33	5.392	33.33	57.14
shr	10362	50.19	50.14	14.88	18.83	83.58
roa	10362	0.0390	0.0370	0.0670	-0.235	0.228
lev	10362	0.410	0.400	0.201	0.0500	0.949
growth	10362	0.161	0.105	0.387	-0.546	2.486
size	10362	22.16	22.06	1.181	19.70	25.55

Table 3 presents the correlation coefficients of the main variables in this study. The correlation coefficient between enterprise digital transformation and green technology innovation is 0.338. The correlation coefficients between absorptive capacity, innovation capability, adaptive capacity, and enterprise digital transformation are 0.027, 0.087, and 0.206, respectively. These correlation coefficients pass the significance test at the 1% level, indicating a positive correlation between enterprise digital transformation and both green technology innovation and dynamic capabilities. The correlation coefficients between absorptive capacity, innovation capability, adaptive capacity, and green technology innovation are 0.028, 0.079, and 0.149, respectively. These correlation coefficients also pass the significance test at the 1% level, suggesting that stronger dynamic capabilities are conducive to promoting green technology innovation. Furthermore, the correlation coefficients among the main variables are all below 0.5, and the average VIF value is 1.33, well below the critical value of 10, indicating no severe multicollinearity issues in the research model.

Table 3. Correlation coefficients of major variables.

Variable	**grepat**	**dti**	**Cap_ab**	**Cap_in**	**Cap_ad**
grepat	1				
dti	0.338***	1			
Cap_ab	0.028***	0.027***	1		
Cap_in	0.079***	0.087***	0.213***	1	
Cap_ad	0.149***	0.206***	-0.205***	0.0040	1

4.2. Test of Principal Effect and Intermediate Effect

Regression analysis was conducted according to the model constructed earlier to examine the influence of enterprise digital transformation on green technology innovation. The results of the main effects and mediating effects tests are shown in Table 4. Based on the regression results in column (1), the regression coefficient between enterprise digital transformation and green technology innovation is 0.038, which is significant at the 1% level, indicating a positive impact of enterprise digital transformation on green technology innovation. By leveraging digital technology applications, companies can access massive information and innovation opportunities, further integrating internal resources to support new technology development and drive green technology innovation. Therefore, H1 is empirically supported. Columns (2), (3), and (4) in the table present the regression

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

results using formula (2), showing significant coefficients at the 1% level, confirming that enterprise digital transformation positively influences the absorptive capacity, innovation capability, and adaptive capacity. Subsequently, formula (3) is employed to test the mediating effects of absorptive capacity, innovation capability, and adaptive capacity between enterprise digital transformation and green technology innovation. As shown in column (5), the regression coefficient of enterprise digital transformation is 0.037, and the coefficient for absorptive capacity is 0.680, both significant at the 1% level, indicating preliminary support for the mediating effect of absorptive capacity between digital transformation and green technology innovation, i.e., H2a is preliminarily supported. Further incorporating innovation capability, the regression results in column (6) show a regression coefficient of 0.016 for enterprise digital transformation and 0.021 for innovation capability, both significant at the 1% level, suggesting preliminary support for the mediating effect of innovation capability between digital transformation and green technology innovation, i.e., H2b is preliminarily supported. Then, with the inclusion of adaptive capacity, the regression results in column (7) reveal a regression coefficient of 0.037 for enterprise digital transformation and 0.146 for adaptive capacity, both significant at the 1% level, indicating preliminary support for the mediating effect of adaptive capacity between digital transformation and green technology innovation, i.e., H2c is preliminarily supported.

Table 4. Test of principal and intermediate effects (sequential test method).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	**grepat**	**Cap_ab**	**Cap_in**	**Cap_ad**	**grepat**	**grepat**	**grepat**
dti	0.038***	0.001***	0.007***	0.005***	0.016***	0.016***	0.037***
	(20.26)	(8.94)	(4.47)	(13.46)	(4.32)	(4.34)	(19.71)
ownership	0.327***	-0.005*	-0.015	0.112***	0.159*	0.165*	0.311***
	(7.76)	(-1.95)	(-0.43)	(13.75)	(1.82)	(1.88)	(7.31)
age	-0.023***	0.001***	0.003	-0.017***	-0.003	-0.003	-0.020***
	(-6.64)	(6.59)	(0.97)	(-25.32)	(-0.33)	(-0.33)	(-5.75)
director	0.004	-0.000	-0.005**	0.001	0.005	0.005	0.004
	(1.24)	(-1.49)	(-2.01)	(0.93)	(1.41)	(1.39)	(1.21)
shr	-0.010***	-0.000***	0.001	-0.001***	-0.005*	-0.005**	-0.009***
	(-7.95)	(-4.68)	(1.28)	(-4.25)	(-1.94)	(-2.27)	(-7.82)
roa	-0.308	-0.064***	-1.307***	0.947***	-0.230	-0.234	-0.445
	(-1.05)	(-3.72)	(-5.55)	(16.70)	(-0.93)	(-0.95)	(-1.50)
lev	0.600***	0.034***	-0.336***	-0.204***	-0.027	0.030	0.630***
	(5.71)	(5.44)	(-3.97)	(-10.00)	(-0.18)	(0.21)	(5.97)
growth	-0.066	-0.003	-0.373***	-0.121***	-0.049*	-0.055*	-0.048
	(-1.48)	(-1.32)	(-10.41)	(-14.03)	(-1.68)	(-1.84)	(-1.07)
size	0.582***	-0.023***	0.027*	0.089***	0.390***	0.371***	0.569***
	(32.65)	(-21.90)	(1.86)	(25.68)	(8.87)	(8.59)	(30.96)
Cap_ab					0.680***		
					(4.30)		
Cap_in						0.021**	
						(2.02)	
Cap_ad							0.146***
							(2.87)
Constant	12.631***	0.537***	-0.496	2.591***	8.224***	7.680***	12.254***

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

	(-33.29)	(23.98)	(-1.62)	(-35.22)	(-8.75)	(-8.42)	(-30.52)
Industry	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES
R-squared	0.318	0.207	0.067	0.232	0.357	0.355	0.318
Observations	10,362	10,362	10,362	10,362	10,362	10,362	10,362

Note: t values in brackets, *** p<0.01, ** p<0.05, * p<0.1. The same as.

The above tests were conducted using a sequential method. However, the stepwise method has limitations in detecting significant mediating effects due to its low statistical power. To address this issue, this study adopts the mediation testing procedure proposed by WEN and YE (2014) and employs the non-parametric percentile bootstrap method to generate multiple "new samples" by repeatedly sampling the original sample data. Statistical analysis is then performed on these "new samples" to obtain more accurate parameter estimates. The number of bootstrap samples is set to 5000, and the results are presented in Table 5. The confidence intervals for the direct effects and indirect effects of absorptive capacity, innovation capability, and adaptive capacity do not include zero, further confirming the significance of the mediating effects.

Table 5. Mediation effect test results (Bootstrap method).

variables	effect	Coef.	std.e	z	P>|z|	95% confidence interval	
						confidence upper limit	Confidence lower limit
Cap_ab	Indirect	0.0005941	0.0001141	5.21	0.000	0.0003706	0.0008177
	direct	0.0541258	0.0017649	30.67	0.000	0.0506666	0.057585
Cap_in	Indirect	0.0004704	0.0001395	3.37	0.001	0.0001969	0.0007439
	direct	0.0542496	0.0017607	30.81	0.000	0.0507986	0.0577005
Cap_ad	Indirect	0.001211	0.0003074	3.94	0.000	0.0006085	0.0018134
	direct	0.053509	0.0017928	29.85	0.000	0.0499951	0.0570228

4.3. Robustness Checks

The current statistical analysis of green patents in enterprises is not comprehensive, with significant variations in the number of green patent citations or substantial data gaps among listed companies. Therefore, we chose the more comprehensive and indicative metric of the number of green patent applications as a replacement for the dependent variable for further analysis of corporate green technological innovation capabilities. To ensure the reliability of the research results, we conducted the following robustness tests, as shown in Table 6. To mitigate the impact of bias on the results, the natural logarithm was taken after adding 1 to the total application quantity, denoted as lnpat. In the first column, the regression coefficient of corporate digital transformation is 0.03 and is significant at the 1% level. In columns (2), (3), and (4), the regression coefficients for absorptive capacity, innovation capability, and utilization capacity are 0.680, 0.019, and 0.103, respectively. Absorptive capacity and adaptive capacity are significant at the 1% level, while innovation capability is significant at the 5% level. This regression result is consistent with the baseline regression results, indicating that even after changing the measurement method of the dependent variable, corporate digital transformation continues to positively influence green technological innovation, and dynamic capabilities still play a mediating role.

Table 6. Change the explanatory variable result.

VARIABLES	(1) lnpat	(2) lnpat	(3) lnpat3	(4) lnpat	(5) grepat	(6) grepat

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

L.dti					0.0424***	0.0445***
					(31.0648)	(29.8066)
dti	0.030***	0.016***	0.030***	0.029***	0.1511***	0.1927***
	(20.96)	(4.32)	(20.85)	(20.43)	(4.4461)	(5.2257)
ownership	0.218***	0.159*	0.218***	0.206***	-0.0017	-0.0038
	(6.86)	(1.82)	(6.87)	(6.44)	(-0.6595)	(-1.3881)
age	-0.016***	-0.003	-0.016***	-0.014***	0.0026	0.0023
	(-6.32)	(-0.33)	(-6.34)	(-5.48)	(1.0538)	(0.8603)
director	0.004*	0.005	0.004*	0.004	-0.0077***	-0.0086***
	(1.65)	(1.41)	(1.69)	(1.62)	(-7.7778)	(-7.9452)
shr	-0.006***	-0.005*	-0.006***	-0.006***	-0.7961***	-0.6078**
	(-7.10)	(-1.94)	(-7.13)	(-6.99)	(-3.3092)	(-2.3495)
roa	-0.213	-0.230	-0.187	-0.310	0.3851***	0.4919***
	(-0.97)	(-0.93)	(-0.85)	(-1.39)	(4.4967)	(5.2827)
lev	0.441***	-0.027	0.447***	0.462***	-0.0051	-0.0269
	(5.58)	(-0.18)	(5.66)	(5.82)	(-0.1418)	(-0.6891)
growth	-0.079**	-0.049*	-0.072**	-0.066**	0.5118***	0.5283***
	(-2.36)	(-1.68)	(-2.13)	(-1.96)	(33.9357)	(32.3925)
size	0.450***	0.390***	0.450***	0.441***	0.1511***	0.1927***
	(33.54)	(8.87)	(33.50)	(31.86)	(4.4461)	(5.2257)
Cap_ab		0.680***			0.9933***	1.1156***
		(4.30)			(6.6586)	(6.5506)
Cap_in			0.019**		0.0289***	0.0271**
			(2.11)		(2.6826)	(2.2882)
Cap_ad				0.103***	0.1673***	0.1736***
				(2.71)	0.9933***	1.1156***
Constant	-9.974***	-8.224***	-9.965***	-9.706***	-11.7015***	-12.0651***
	(-34.94)	(-8.75)	(-34.91)	(-32.13)	(-35.8210)	(-33.9916)
Industry	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Observations	10,362	10,362	10,362	10,362	10,362	10,362
R-squared	0.330	0.357	0.330	0.330	0.298	0.299

4.4. Endogeneity Problem

Combining the analysis in this paper with existing research results, it is evident that corporate digital transformation can promote the improvement of the level of green technological innovation. The enhancement of green technological innovation capabilities can contribute to cost reduction and efficiency improvement in manufacturing enterprises, potentially further driving corporate digital transformation. There may exist a mutually reinforcing relationship between the two. To address the potential endogeneity issue arising from the reciprocal causation between the explanatory variable and the dependent variable, this paper conducted regression analyses with lagged one-period and lagged two-period treatment for the explanatory variable, corporate digital transformation. The regression results are presented in Table 6, columns (5) and (6). It can be observed that the regression coefficients for corporate digital transformation, dynamic capabilities, and green technological innovation are consistent with the significance and patterns observed in Table 4, indicating that the

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 January 2024 doi:10.20944/preprints202401.0438.v1

impact of reciprocal causation on the research conclusions is minimal. In conclusion, the finding that corporate digital transformation positively influences green technological innovation is robust and reliable.

5. Further Discussion

5.1. Heterogeneity Analysis of Heavy Polluting Industries

The heavy polluting industry plays a critical role in environmental protection and sustainable development. Its production activities are typically associated with higher environmental impact and carbon emissions, and the impact of environmental regulations is more pronounced. Industries with high pollution levels exhibit a stronger inclination toward green technological innovation. Therefore, this paper anticipates a more significant impact of corporate digital transformation on green technological innovation in enterprises within the heavy polluting industry.

To validate this viewpoint, based on the "Catalog Management Directory for Environmental Inspection of Listed Companies" formulated by the Chinese Ministry of Environmental Protection in 2008, 16 industries, including coal, mining, textiles, leather, papermaking, petrochemicals, pharmaceuticals, chemicals, metallurgy, and thermal power, are categorized as heavy polluting industries. Others are classified as non-heavy polluting industries. The overall sample is divided into two groups for heterogeneous analysis: heavy polluting industries and non-heavy polluting industries.

The results of the analysis are presented in Table 7. As indicated in column (1), the regression coefficient for corporate digital transformation in the heavy polluting sample group is 0.047 and significant at the 1% level. Similarly, column (2) reveals a regression coefficient of 0.04 for corporate digital transformation in the non-heavy polluting sample group, also significant at the 1% level. From the analysis, it is evident that compared to non-heavy polluting industries, the promotion effect of corporate digital transformation on green technological innovation is more pronounced in heavy polluting industries.

Table 7. Heterogeneity test.

	Heavy Polluting	**Non-heavy Polluting**	**High-Tech**	**Non-High-Tech**
	(1)	(2)	(3)	(4)
VARIABLES	grepat	grepat	grepat	grepat
dti	0.047***	0.040***	0.044***	0.039***
	(12.09)	(17.29)	(17.72)	(11.40)
Contorl	YES	YES	YES	YES
Constant	-0.349**	-0.078	-0.240***	0.030
	(-2.34)	(-0.89)	(-2.58)	(0.23)
Observations	2,563	7,797	6,511	3,850
R-squared	0.199	0.189	0.204	0.171
Industry	YES	YES	YES	YES
Year	YES	YES	YES	YES

t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

5.2. Heterogeneity Analysis of High-Tech Industry

Innovation is the core of survival and development for high-tech enterprises. These enterprises often possess strong technological foundations and research and development capabilities. Digital

 doi:10.20944/preprints202401.0438.v1

transformation enables more effective integration and utilization of these technological resources. Through digital technology, enterprises can conduct more precise research and development, enhance R&D efficiency, and drive the development of products and services with a greener and more innovative nature. Therefore, this paper anticipates a more pronounced impact of corporate digital transformation on green technological innovation in high-tech industry enterprises.

To validate this hypothesis, the paper utilizes data from the CSMAR database regarding the qualification recognition information of listed companies. The overall sample is divided into two groups for heterogeneous analysis: high-tech enterprises and non-high-tech enterprises.

The results of the analysis are presented in Table 7. As indicated in column (3), the regression coefficient for corporate digital transformation in the high-tech sample group is 0.044 and significant at the 1% level. Similarly, column (4) reveals a regression coefficient of 0.039 for corporate digital transformation in the non-high-tech sample group, also significant at the 1% level. From the analysis, it is evident that compared to non-high-tech industries, the promotion effect of corporate digital transformation on green technological innovation is more pronounced in high-tech industries.

6. Discussion

The empirical analysis results in this study are generally consistent with the research expectations, indicating that digital transformation in enterprises plays a significant role in promoting green technological innovation, with dynamic capabilities acting as an intermediary. This conclusion aligns with findings from other studies, and the support obtained through robustness analysis further strengthens our findings. Heterogeneity analysis focusing on heavily polluting and high-tech enterprises reveals that organizations can effectively enhance their dynamic capabilities during the process of digital transformation, thereby elevating their innovation levels and intensifying their attention to green technological innovation.

However, there are still some limitations in this paper that need further refinement in future research. Firstly, this study takes dynamic capabilities as a starting point to explore the mediating relationship between enterprise digital transformation and green technological innovation. Future research could delve into the specific impact mechanisms of digital transformation on green technological innovation and how green technological innovation supports the development of enterprise digital transformation. Secondly, this paper selectively focuses on representative enterprises in the manufacturing industry with regard to green technological innovation. Future research could expand to other industries such as the service sector or examine enterprises in other countries to enhance the broad applicability of the study.

7. Conclusions and Recommendation

7.1. Conclusions

Against the backdrop of the Chinese government's vigorous promotion of the "Dual Carbon" strategy and the flourishing development of digital transformation, China's manufacturing enterprises are facing significant challenges in achieving high-quality economic development and driving green technology innovation. In this study, based on data from listed manufacturing companies in China from 2011 to 2021, and using the measure of green patent citations, we empirically examine the relationship between enterprise digital transformation and green technology innovation, as well as the mediating role of dynamic capabilities. The main conclusions drawn from theoretical and empirical analyses are as follows: First, enterprise digital transformation enhances the capabilities of information acquisition, integration, and sharing, optimizes resource allocation, and achieves cost reduction and efficiency improvement, thereby facilitating green technology innovation in enterprises. Second, enterprise digital transformation effectively aids enterprises in acquiring and integrating knowledge, keeping pace with market environmental changes, and capturing innovation opportunities. This, in turn, enhances the dynamic capabilities of enterprises (absorptive capacity, innovative capacity, and adaptive capacity). Furthermore, dynamic capabilities play a significant mediating role in the impact of enterprise digital transformation on green technology innovation.

Finally, the results of the heterogeneity analysis indicate that in high-tech enterprises and companies within heavy polluting industries, the promoting effect of corporate digital transformation on green technological innovation is more pronounced.

Overall, these findings highlight the positive relationship between enterprise digital transformation and green technology innovation, as well as the crucial mediating role of dynamic capabilities. These insights are crucial for Chinese manufacturing enterprises as they navigate the pressure of green development and strive for economic growth of high quality.

7.2. Recommendation

The research findings of this study have valuable implications for both businesses and governments. For businesses, the wave of digital economy development is inevitable, and digital transformation is a necessary path for survival and growth. However, while undergoing transformation, enterprises should prioritize the environmental impact of digital transformation, placing environmental protection in a more prominent position and making green technology innovation an important goal of digital transformation. This is particularly crucial for manufacturing enterprises as they face stricter requirements imposed by green economic development policies. They should focus on long-term benefits and actively pursue the development of green innovative technologies. Furthermore, it is important to emphasize the cultivation of dynamic capabilities. Enterprises should leverage digital transformation to enhance their abilities in data acquisition, analysis, and application, enabling them to grasp market dynamics and improve their adaptability to the requirements of digital transformation and green technology innovation. Lastly, enterprises should strengthen collaboration with supply chain partners to collectively promote green technology innovation and reduce environmental risks and burdens throughout the entire industry chain. The supply chain is an integral part of enterprise digital transformation and green technology innovation. By enhancing cooperation with supply chain partners, enterprises can achieve green supply chain management, collaborative research and development, shared responsibilities, information sharing, and risk management. This will result in accessing more resources and support for digital transformation and green technology innovation, facilitating the realization of their objectives.

For the government, it is essential to improve and implement relevant policies and regulations. The primary challenge faced by businesses in green technology innovation is inadequate resource investment, resulting in significant financial pressure. The government should develop policies and regulations that favor enterprise digital transformation and green technology innovation, providing financial and technological support to encourage businesses in pursuing digital transformation and green technology innovation. Additionally, the government should strengthen the development of related infrastructure. It should further invest in digital infrastructure to reduce the cost of enterprise digital transformation and enhance the prevalence and coverage of digital infrastructure, providing the foundational conditions for digital transformation. Furthermore, integrating digital and green infrastructure can be promoted to facilitate their interconnection and promote sustainable development for businesses. Lastly, it is crucial to enhance technical support and talent development. Talents are the driving force behind innovation, and the government should strengthen technical support and talent cultivation for enterprise digital transformation and green technology innovation. This can be achieved by establishing centers for technological innovation, talent training centers, and other initiatives dedicated to digital transformation and green technology innovation, providing technical consultation and talent support for businesses.

References

1. Agarwal, R, Gao, G (Gordon), DesRoches, C, and Jha, AK (2010) Research Commentary---The Digital Transformation of Healthcare: Current Status and the Road Ahead. *Information Systems Research*, **21**(4), 796–809. doi:10.1287/isre.1100.0327.
2. Aguilera-Caracuel, J, and Ortiz-de-Mandojana, N (2013) Green Innovation and Financial Performance: An Institutional Approach. *Organization & Environment*, **26**(4), 365–385. doi:10.1177/1086026613507931.
3. Alder, S, Shao, L, and Zilibotti, F (2012) *The Effect of Economic Reform and Industrial Policy in a Panel of Chinese*

Cities (DEGIT Conference Paper), DEGIT, Dynamics, Economic Growth, and International Trade. Retrieved from https://econpapers.repec.org/paper/degconpap/c017_5f061.htm

4. Berrone, P, Fosfuri, A, Gelabert, L, and Gomez-Mejia, LR (2013) Necessity as the mother of 'green' inventions: Institutional pressures and environmental innovations: Necessity as the Mother of 'Green' Inventions. *Strategic Management Journal*, **34**(8), 891–909. doi:10.1002/smj.2041.
5. Braun, E, and Wield, D (2007) Regulation as a means for the social control of technology. *Technology Analysis & Strategic Management*. doi:10.1080/09537329408524171.
6. Cleff, T, and Rennings, K (1999) Determinants of environmental product and process innovation. *European Environment*, **9**(5), 191–201. doi:10.1002/(SICI)1099-0976(199909/10)9:5<191::AID-EET201>3.0.CO;2-M.
7. Cui, R, Wang, J, Xue, Y, and Liang, H (2020) Interorganizational learning, green knowledge integration capability and green innovation. *European Journal of Innovation Management*, **ahead-of-print**. doi:10.1108/EJIM-11-2019-0325.
8. Daniel Ellström, Johan Holtström, Emma Berg, and Cecilia Josefsson (2021) Dynamic capabilities for digital transformation. *Journal of Strategy and Management*, **15**(2), 272–286. doi:10.1108/JSMA-04-2021-0089.
9. Demartini, M, Evans, S, and Tonelli, F (2019) Digitalization Technologies for Industrial Sustainability. *Procedia Manufacturing*, **33**, 264–271. doi:10.1016/j.promfg.2019.04.032.
10. Eechoud, TV, and Ganzaroli, A (2023) Exploring the role of dynamic capabilities in digital circular business model innovation: Results from a grounded systematic inductive analysis of 7 case studies. *Journal of Cleaner Production*, **401**, 136665. doi:10.1016/j.jclepro.2023.136665.
11. Faria, PD, Lima, F, and Santos, R (2010) Cooperation in innovation activities: The importance of partners. *Research Policy*, **39**(8), 1082–1092. doi:10.1016/j.respol.2010.05.003.
12. Fei W, Huizhi H, Huiyan L, and Xiaoyi R (2021) Enterprise Digital Transformation and Capital Market Performance: Empirical Evidence from Stock Liquidity. *Management World*, **37**(7), 130-144+10. doi:10.19744/j.cnki.11-1235/f.2021.0097.
13. Feng, C, and Ma, R (2020) Identification of the factors that influence service innovation in manufacturing enterprises by using the fuzzy DEMATEL method. *Journal of Cleaner Production*, **253**, 120002. doi:10.1016/j.jclepro.2020.120002.
14. Feng, H, Wang, F, Song, G, and Liu, L (2022) Digital Transformation on Enterprise Green Innovation: Effect and Transmission Mechanism. *International Journal of Environmental Research and Public Health*, **19**(17), 10614. doi:10.3390/ijerph191710614.
15. Ferreira, J, Coelho, A, and Moutinho, L (2020) Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation. *Technovation*, **92–93**, 102061. doi:10.1016/j.technovation.2018.11.004.
16. Gregory Vial (2019) Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, **28**(2), 118–144. doi:10.1016/j.jsis.2019.01.003.
17. Günther, WA, Mehrizi, MHR, Huysman, M, and Feldberg, F (2017) Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, **26**(3), 191–209. doi:10.1016/j.jsis.2017.07.003.
18. Guo F, Shangguang Y, and Zeyang C (2023) Does Digital Transformation of Enterprises Improve the Quantity and Quality of Green Technology Innovation？ Text Analysis Based on Annual Reports of Chinese Listed Companies. *South China Journal of Economics*, (2), 146–162. doi:10.19592/j.cnki.scje.400349.
19. Guo, Y, Xia, X, Zhang, S, and Zhang, D (2018) Environmental Regulation, Government R&D Funding and Green Technology Innovation: Evidence from China Provincial Data. *Sustainability*, **10**(4), 940. doi:10.3390/su10040940.
20. Hanelt, A, Bohnsack, R, Marz, D, and Marante, CA (2021) A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change. *Journal of Management Studies*, **58**(5), 1159–1197. doi:10.1111/joms.12639.
21. Hartono, A, and Kusumawardhani, R (2019) Innovation Barriers and Their Impact on Innovation: Evidence from Indonesian Manufacturing Firms. *Global Business Review*, **20**(5), 1196–1213. doi:10.1177/0972150918801647.
22. Helfat, CE, and Raubitschek, RS (2018) Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, **47**(8), 1391–1399. doi:10.1016/j.respol.2018.01.019.
23. Huang, L, Wang, C, Chin, T, Huang, J, and Cheng, X (2022) Technological knowledge coupling and green innovation in manufacturing firms: Moderating roles of mimetic pressure and environmental identity. *International Journal of Production Economics*, **248**, 108482. doi:10.1016/j.ijpe.2022.108482.
24. Jichang Z, and Jing L (2022) Digital Transformation，Dynamic Capability，and Enterprise Innovation Performance: Empirical Evidence from High－Tech Listed Companies. *Economy and Management*, **36**(3), 74–83.

25. Lai, K, Feng, Y, and Zhu, Q (2023) Digital transformation for green supply chain innovation in manufacturing operations. *Transportation Research Part E: Logistics and Transportation Review*, **175**, 103145. doi:10.1016/j.tre.2023.103145.
26. Lee, C-C, Qin, S, and Li, Y (2022) Does industrial robot application promote green technology innovation in the manufacturing industry? *Technological Forecasting and Social Change*, **183**, 121893. doi:10.1016/j.techfore.2022.121893.
27. Li, G, Li, X, and Huo, L (2023) Digital economy, spatial spillover and industrial green innovation efficiency: Empirical evidence from China. *Heliyon*, **9**(1), e12875. doi:10.1016/j.heliyon.2023.e12875.
28. Liao, J (Jon), Kickul, JR, and Ma, H (2009) Organizational Dynamic Capability and Innovation: An Empirical Examination of Internet Firms. *Journal of Small Business Management*, **47**(3), 263–286. doi:10.1111/j.1540-627X.2009.00271.x.
29. Lin, B, and Ma, R (2022) How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective. *Journal of Environmental Management*, **320**, 115833. doi:10.1016/j.jenvman.2022.115833.
30. Liu, X, Liu, F, and Ren, X (2023) Firms' digitalization in manufacturing and the structure and direction of green innovation. *Journal of Environmental Management*, **335**, 117525. doi:10.1016/j.jenvman.2023.117525.
31. Maheshwari, A (2019) *Digital Transformation: Building Intelligent Enterprises*, John Wiley & Sons.
32. Nielsen, AP (2006) Understanding dynamic capabilities through knowledge management. *Journal of Knowledge Management*, **10**(4), 59–71. doi:10.1108/13673270610679363.
33. Nieves, J, and Haller, S (2014) Building dynamic capabilities through knowledge resources. *Tourism Management*, **40**, 224–232. doi:10.1016/j.tourman.2013.06.010.
34. Omonijo, ON, and Yunsheng, Z (2022) Impact mechanism of technological innovation by Chinese companies on CSR in Africa mobile communication industry. *Innovation and Green Development*, **1**(2), 100005. doi:10.1016/j.igd.2022.100005.
35. Porter, ME, and Linde, CVD (1995) Toward a New Conception of the Environment-Competitiveness Relationship. *Journal of Economic Perspectives*, **9**(4), 97–118. doi:10.1257/jep.9.4.97.
36. Provost, F, and Fawcett, T (2013) Data Science and its Relationship to Big Data and Data-Driven Decision Making. *Big Data*, **1**(1), 51–59. doi:10.1089/big.2013.1508.
37. Ren, S, Sun, H, and Zhang, T (2021) Do environmental subsidies spur environmental innovation? Empirical evidence from Chinese listed firms. *Technological Forecasting and Social Change*, **173**, 121123. doi:10.1016/j.techfore.2021.121123.
38. Sagiroglu, S, and Sinanc, D (2013) Big data: A review. In *2013 International Conference on Collaboration Technologies and Systems (CTS)*, San Diego, CA, USA: IEEE, , 42–47. doi:10.1109/CTS.2013.6567202.
39. Sarkar, B, Ullah, M, and Sarkar, M (2022) Environmental and economic sustainability through innovative green products by remanufacturing. *Journal of Cleaner Production*, **332**, 129813. doi:10.1016/j.jclepro.2021.129813.
40. Song D, Wenbo Z, and Hai D (2022) Can Firm Digitalization Promote Green Technological Innovation? An Examination Based on Listed Companies in Heavy Pollution Industries. *Journal of Finance and Economics*, **48**(04), 34–48. doi:10.16538/j.cnki.jfe.20211218.304.
41. Stock, GN, Greis, NP, and Fischer, WA (2002) Firm size and dynamic technological innovation. *Technovation*, **22**(9), 537–549. doi:10.1016/S0166-4972(01)00061-X.
42. Su, X, Pan, C, Zhou, S, and Zhong, X (2022) Threshold effect of green credit on firms' green technology innovation: Is environmental information disclosure important? *Journal of Cleaner Production*, **380**, 134945. doi:10.1016/j.jclepro.2022.134945.
43. Teece, DJ (2007) Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, **28**(13), 1319–1350. doi:10.1002/smj.640.
44. Teece, DJ, Pisano, G, and Shuen, A (2009) Dynamic capabilities and strategic management. *Strategic Management Journal*, págs. 509-533. doi:10.1002/(SICI)1097-0266(199708)18:73.0.CO;2-Z.
45. Vaska, S, Massaro, M, Bagarotto, EM, and Mas, FD (2021) The Digital Transformation of Business Model Innovation: A Structured Literature Review. *Frontiers in Psychology*, **11**. doi:10.3389/fpsyg.2020.539363.
46. Verhoef, PC, Broekhuizen, T, Bart, Y, … Haenlein, M (2021) Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, **122**, 889–901. doi:10.1016/j.jbusres.2019.09.022.
47. Vogel, R, and Güttel, W (2013) The Dynamic Capability View in Strategic Management: A Bibliometric Review. *International Journal of Management Reviews*. doi:10.1111/ijmr.12000.
48. Wang, CL, and Ahmed, PK (2007) Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews*. doi:10.1111/j.1468-2370.2007.00201.x.
49. Warner, KSR, and Wäger, M (2019) Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, **52**(3), 326–349. doi:10.1016/j.lrp.2018.12.001.

50. WEN Z, and YE baojuan (2014) Analyses of Mediating Effects: The Development of Methods and Models. *Advances in Psychological Science*, **22**(5), 731–745.
51. Xue, L, Zhang, Q, Zhang, X, and Li, C (2022) Can Digital Transformation Promote Green Technology Innovation? *Sustainability*, **14**(12), 7497. doi:10.3390/su14127497.
52. Yi-ming L, and Yao W (2022) Study on the impact of corporate digitalization on green technology innovation. *Science-Technology and Management*, **24**(06), 85–96. doi:10.16315/j.stm.2022.06.005.
53. Yu, H, Wang, J, Hou, J, Yu, B, and Pan, Y (2023) The effect of economic growth pressure on green technology innovation: Do environmental regulation, government support, and financial development matter? *Journal of Environmental Management*, **330**, 117172. doi:10.1016/j.jenvman.2022.117172.
54. Zahra, SA, and George, G (2002) Absorptive Capacity: A Review, Reconceptualization, and Extension. *The Academy of Management Review*, **27**(2), 185. doi:10.2307/4134351.
55. ZhaoFeng, Tienan W, and Yu W (2016) External Technology Acquisition in Open Innovation and Product Diversification: The Moderating Effect of Dynamic Capabilities. *Business Review*, **28**(6), 76-85+99. doi:10.14120/j.cnki.cn11-5057/f.2016.06.008.
56. Zhou, S, Zhou, A, Feng, J, and Jiang, S (2017) Dynamic capabilities and organizational performance: The mediating role of innovation. *Journal of Management & Organization*, **25**, 1–17. doi:10.1017/jmo.2017.20.

Note: t values in brackets, *** p<0.01, ** p<0.05, * p<0.1. The same as