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Empirical Evidence from Listed Chinese Manufacturing Companies

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Abstract

In the current era of digital economy, green innovation has gradually become an important symbol of the green development of enterprises. This paper accelerates the coordinated development of digitalization and "greenization" by using panel data from China's A-share-listed manufacturing companies from 2007 to 2019 to study the relationship between digital transformation and breakthrough green innovation. The empirical results reveal that the source of the increase in the number of green patents promoted by digital transformation is not the breakthrough innovation reflecting quality and effect, but demonstrates technical similarity. Further analysis demonstrates that enterprises in technology-intensive industries and strong market competition environment will be more inclined toward breakthrough green innovation after a digital transformation. This study empirically supports green transformations of manufacturing enterprises while providing new ideas for cultivating enterprises to choose high-quality green innovation modes.

Keywords: Breakthrough green innovation, digital transformation, manufacturing industries, dual innovation

Introduction

Between 2012 and 2021, the added value of China's manufacturing industry increased from 1.698 billion yuan to 31.4 trillion yuan, or 30% worldwide. With accelerated digitalization in the manufacturing industry, the numerical control rate of processes in key areas reached 55.3%, and the penetration rate of digital R&D and design tools reached 74.7%,[1] providing a strong impetus for the sustainable, healthy development of both the economy and society. However, the rapid expansion of China's manufacturing scale has also created severely high energy consumption and major pollutant emissions. Green innovation plays a crucial role in enterprise greening and serves as a sustainable development model aligned with China's goals of building an ecological civilization. In China's current economic transformation, manufacturing enterprises must urgently break through institutional and efficiency-related dilemmas with assistance from high-quality green innovation to achieve sustainable development (Xie and Han, 2022). Under the strategic

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[1] Manufacturing-related growth statistics are sourced from the Ministry of Industry and Information Technology of the People's Republic of China.

guidance of the nation's "dual and coordinated development,"[2] digitalization-enabled green development has become the only way to promote mutually beneficial social, economic, and environmental benefits.

The State Intellectual Property Office (SIPO) indicates that the number of green patent applications in China increased from 27,000 to 557,000 between 2007 and 2020, with an average annual growth rate of 26.2%[3]. Tao et al. (2021) measured the quality of green innovation through the degrees of differences in knowledge given the green patent International Patent Classification (IPC) group level; they noted that the average quality of green innovation in China was 0.37 from 2000 to 2005, but this decreased to 0.33 from 2006 to 2015.[4] Therefore, the difference in degrees of knowledge among China's green patents has narrowed, and this innovation tends to be more homogeneous, which is not conducive to improving the quality of green innovation. According to the dual innovation theory, enterprises' innovation activities can be divided into two types: incremental innovation, which reflects the innovation quantity and efficiency; and breakthrough innovation, which reflects the innovation's quality and effect (Manso, 2011; Forés and Camisón, 2016). Compared with incremental innovation, breakthrough innovation emphasizes that enterprises stop depending on existing knowledge and actively explore unknown knowledge areas to achieve breakthrough innovation results (Byun et al., 2020). Currently, highly efficient breakthrough innovations are an important way to alleviate downward economic pressure and help enterprises overtake the "curve" (Zhuang et al., 2020); this is also at the core of corporate creativity (Forés and Camisón, 2016). High-quality breakthroughs are key for current manufacturing enterprises to achieve green development. This is especially the case given the current quantity of green innovation activities in China, but as the quality of green innovation is insufficient, studying the influencing factors affecting enterprises' breakthrough green innovation is of great practical significance for improving China's green innovation quality and strengthening the country with innovation.

In theory, digital technologies are characterized by openness (Nambisan et al., 2019), which can help enterprises expand the scope of their searches for external knowledge and improve their ability to combine the existing information to create new knowledge (Wu et al., 2020). In the context of the digital age, digital technology can be characterized as disruptive, profoundly changing the production and operation model, as well as the market transaction paradigm (Vial, 2019). Therefore, manufacturing enterprises' digital transformation may trigger innovation activities (Acemoglu et al., 2022); while this will promote breakthrough green innovation and enterprises' long-term competitive advantage, few empirical studies have explored this problem of disruptive digital technology and the mechanism behind it.

In recent years, with the rapid development of the digital economy, the digital transformation's impact on green innovation quality has become a prevalent issue of academic concern. However, existing empirical research has not reached a unified conclusion. On the one hand, enterprises' application of digital technologies can highlight any competitive advantage in green innovation (Mubarak et al., 2021). Consequently, digital transformation has a dual effect on enterprises' green innovation performance. According to Shen and Tan (2022), it leads to an incremental improvement in quality, while Wang et al. (2022) suggest that it enhances the quality of green innovation activities more than the quantity. On the other hand, studies also observe that advances in digital technology may increase enterprises' extraction of resources and energy consumption, which may decrease the quality of their green innovation (Wang et al., 2019). In summary, there is limited research discussing the impact of digitalization on the quality of green technological innovation, with a focus primarily on the number of green patent applications. Literature lacks micro-evidence from a green technology perspective to explore enterprises' breakthrough green innovation, and especially innovation that deviates from the original technological field under the green development goal of digital transformation. Thus, it is difficult to accurately grasp the digital transformation's mechanism of impact on the green innovation business model of enterprises.

[2] The White Paper on Coordinated Development of Digital Greening (2023) issued by the China Academy of Information and Communications Technology observed that the scientific connotation of the "coordinated development of digitalization and industrialization" refers to the digitalization and green upgrading of economic and social production and life to achieve comprehensive and high-quality development.

3 The State Intellectual Property Office is a state office under the administration of the State Administration for Market Regulation. Mainly responsible for drafting and organizing the implementation of national intellectual property strategy, intellectual property examination and registration and administrative adjudication.

[4] This paper calculates green innovation quality data based on relevant information from the BvD patent database.

Subsequently, this paper uses green patent data from China's A-share-listed manufacturing enterprises from 2010 to 2019 to empirically investigate the following issues: First, it examines the relationship between manufacturing enterprises' digital transformation and their green innovation model. Based on the theory of dual innovation, this paper reveals two categories of enterprises' green innovation activities: incremental and breakthrough innovation. It then further explores whether enterprises' digital transformation has indeed promoted breakthrough green innovation in broadening the original technological field.

Second, this paper considers both theoretical and empirical perspectives to explore the mechanism by which manufacturing enterprises' digital transformation has impacted green innovation models. If the empirical results reveal that enterprises' digital transformations promote breakthrough green innovation, the impact mechanism must then be determined. Otherwise, if it is discovered that digital transformations do not promote enterprises' breakthrough green innovation, such a result must be explained. Exploring economic mechanisms will better convey the digital transformation's impact on green innovation models while providing a reference for future business management decisions.

Third, this paper considers the previously mentioned research to discuss the heterogeneity of different enterprises' digital transformations and their impacts on green innovation models. This will provide new ideas for the government in forming green innovation incentive policies.

Literature Review

Enterprises' Digital Transformation

The concept of digital transformation is currently a popular topic in academia. Some scholars have defined digital transformations as those that involve the use of technology to change operational efficiency and business performance significantly (Westerman and Bonnet, 2015), while others believe that such transformations pertain to digital technologies' transformative or disruptive impacts on businesses (Nambisan et al., 2019).

Accenture's *2021 China Enterprise Digital Transformation Index Research* report notes that only 16% of Chinese enterprises have achieved remarkable digital transformations. In comparing the digital application and promotion speed within China's service industry to that of its manufacturing industry, although the latter is a leading force in China's economic development, its digital transformation process is significantly lagging. The quantitative literature on manufacturing enterprises' digital transformations primarily focuses on economic impacts, such as the impacts on enterprises' key business outcomes (Yi et al., 2021), flexible management (Enrique et al., 2022), total factor productivity (Yuan et al., 2021), innovation efficiency (Yang et al., 2022a), and business service transformations (Zhao, 2021), among other factors with significant, positive effects.

Green Innovation

Green innovation emphasizes the realization of sustainable economic development through new processes and products that reduce pollution and resource consumption (Aghion et al., 2022). As a new innovation model that can effectively address pollution prevention and control, energy conservation, green technology improvement, and the green management of enterprises (Wang et al., 2019), green innovation can help to improve enterprises' green image while promoting the development of a green society and providing economic benefits (Sun and Sun, 2021).

Although the number of green patent applications in China is increasing, green innovations are still of lesser quality overall, which is primarily reflected in two aspects. First, from a patent-type perspective, few green invention patents have been issued. Tang et al. (2021) calculated that from 2010 to 2019, the number of green utility model patents in China grew much faster than that of green invention patents; specifically, the number of green utility model patents was approximately three times that of green invention patents. Second, when the degree of knowledge difference is measured by classifying the IPC of green patents at a group level, the average value of the quality of green innovations in China was 0.37 from 2000 to 2005, but decreased to 0.33 from 2006 to 2015 (Tao et al., 2021). Therefore, the difference in degrees of knowledge among China's green patents is shrinking, leading to more homogeneous innovations.

Given the rapid development of the digital economy and the construction of a "digital China" in recent years, scholars have continued to focus their research perspectives on applications of digital technology. From a regional perspective, literature has discovered that the development of digital finance promotes enterprises' green innovations by alleviating their financing constraints and reducing their risks (Gu and Gao, 2022). From an enterprise perspective, applying digital technologies has had dual effects. For example, "incremental quality improvement" has occurred in enterprises' green innovation performance (Shen and Tan, 2022). Moreover, an urban, networked infrastructure has helped enterprises develop new technologies by expanding the boundaries of enterprises' innovation and facilitating breakthrough innovations (Shen et al., 2023). Conversely, Li et al. (2021) noted that digital technological progress will encourage enterprises to acquire new production equipment, but in the transition phase of enterprises' digital transformation, resource extraction and energy consumption will increase rapidly increase production, which may reduce enterprises' green innovation activities.

Combining the characteristics of dual and green innovation, enterprises' green innovation activities can be divided into breakthrough green innovation, which breaks the existing green innovation technology path, and incremental green innovation, which further uses the existing green technology path (Li and Zeng, 2021). Breakthrough green innovation involves the reversal and breakthrough of existing green knowledge and technology, which often involves the development of novel green products and processes.

Literature has explored the necessary conditions for breakthrough green innovation from the perspective of a traditional green technology, organization, and environmental framework. However, empirical evidence is still lacking as to whether the digital transformation caused by introducing digital technology in the digital economy era can effectively promote enterprises' breakthrough green innovation.

Digital Transformation and Green Innovation

In recent years, with the development of the digital economy, scholars have increasingly begun to observe digital technology's impacts on green innovation. Among others, El-Kassar and Singh's (2019) questionnaire analysis of 215 companies in the Middle East-North African and Gulf regions indicated that applying digital technologies further strengthened enterprises' competitive advantage by promoting green innovation activities among such companies. Waqas et al. (2021) collected 294 questionnaires from Chinese manufacturing enterprises and used structural equation modeling to evaluate Big Data technologies' impacts on enterprises' environmental performance. These authors noted that green innovation was a positive transmitter in the process of innovating with Big Data analysis technology to improve enterprises' environmental performance. Yang et al. (2022b) found that smart manufacturing in the manufacturing industry can be important in promoting green innovation through the "technology promotion" and "cost reduction" effects. Chin et al. (2022) noted that applying blockchain technology can positively impact green innovation performance, with the ownership of value as a mediator, which is ultimately conducive to achieving a sustainable green economy.

Digitalization based on the application of digital technology has become a key strategic direction for global technological change, and digital transformations, in particular, have become an important path for high-quality economic development. Therefore, enterprises' digital transformations will inevitably disrupt the enterprise management model and even management systems, affecting enterprises' green innovation model (Zhang et al., 2022). Existing literature indicates that digital technology, intelligent manufacturing, and advanced information system applications are the three main digital modes to promote enterprises' green innovation (Jiang et al., 2023). Additionally, enterprises' digital transformation can improve the quantity and quality of green innovation by reducing the cost of debt (Liu et al., 2023) and increasing R&D investments (Feng et al., 2022); this is primarily reflected in the increase in the number of green patent applications and citations. However, some studies suggest that the relationship between the digital economy and corporate green innovation is not a simple linear relationship, but an inverted U-shaped relationship that first promotes then inhibits (Dou and Gao, 2022).

Ultimately, existing studies have generally found that digital transformation has spurred an increase in the number of corporate green innovations. However, these do not distinguish between corporate green innovation models or examine whether the source of the increase in green patents is breakthrough or incremental innovation. If the number of green innovations is due to incremental innovations, then digital transformations do not help facilitate companies' green technology breakthroughs, but only improve existing technologies, and do not help companies' long-term environmentalism. Therefore, it is of great practical importance to study digital transformations' impacts on breakthrough green innovation.

Hypotheses' Development

In theory, digital transformation serves dual roles relative to breakthrough green innovation. On the one hand, it supplies the requisite knowledge and technical resources for breakthrough green innovation by offering cutting-edge digital technologies. On the other hand, both enterprise digitalization and breakthrough green innovation are essential components of corporate strategic decision-making. Consequently, the investments directed toward digital transformations might potentially distort any focus on breakthrough green innovation. Hence, this paper examines both the positive promotion and negative inhibition of enterprises' digital transformation on breakthrough green innovation by elucidating the relationships between the two from both positive and negative perspectives.

The Facilitating Effect

The essence of green innovation is the reorganization and reengineering of knowledge, which involves creating and integrating knowledge in such different technical fields as enterprise production and pollution reduction within the organization (Song et al., 2022). Compared with incremental green innovation, breakthrough green innovation requires enterprises to abandon their familiar knowledge fields and explore new technological fields (Kaplan and Vakili, 2014). From the perspective of the "technology-economy" characteristics of digital technology, digital technology is characterized by openness (Nambisan et al., 2019), effectively reducing the trial-and-error cost of enterprise innovation (Vial, 2019). This can help enterprises expand the scope of their external knowledge search and improve their ability to combine existing knowledge to create new knowledge (Wu et al., 2020; Lanzolla et al., 2021). Therefore, the application of digital technology in digital transformations can improve the efficiency of information processing and circulation and promote the internal integration and external expansion of both old and new resources and capabilities. This can transform production processes, business activities, and business models (Capponi et al., 2022) to improve the efficiency of internal and external knowledge acquisition and resource integration, and, ultimately, allow enterprises to achieve breakthrough green innovation.

The Inhibiting Effect

In reality, green and traditional technological innovations differ, with a "double externality": a positive externality of technical knowledge and negative externality of the environment (Nordhaus, 2021). Green technologies are typically adaptive among different industries, in that innovative enterprises pay all the costs, but do not receive all the market benefits. Although digital transformations can supplement the internal and external knowledge resources required for green innovation, they may exacerbate the technology spillover generated by enterprises engaged in green innovation. Thus, digital transformations reduce enterprises' motivation to engage in relatively high-cost breakthrough innovation.

Regarding the economic consequences of digital transformation, enterprises' extensive application of digital technology will significantly increase their external knowledge or information elements. Further, such applications will make it more difficult for enterprises to identify useful information, or specifically, an "information overload" effect will occur (Capponi et al. 2022; Wang et al., 2022). Enterprises must limit their vision to partial information or information in familiar fields instead of all information or information in fresh fields, thus affecting their management decisions and innovation responsiveness. Therefore, the information overload brought by a digital transformation may hinder management decisions based on long-term interests and further reduce breakthrough green innovation behaviors.

Byun et al. (2020) argue that breakthrough innovations are characterized by a longer investment cycle, higher exit costs, and greater investment risks. *These characteristics necessitate substantial investment resources to support their development.* Clearly, the massive resource input required in applying and integrating digital technologies into enterprises' entire operations and management process will have a crowding-out effect on any strategic upgrading in general, and weaken the necessary resource base for strategic upgrading in particular (Wang et al., 2022). Therefore, the enterprise resources consumed by digital transformations may crowd out more human resources or capital required for breakthrough green innovation—specifically, a "resource crowding" effect may occur. Consequently, enterprises tend to choose low-cost, gradual green innovations with relatively short-term results and abandon any opportunity for breakthrough green innovations. Given this analysis, this paper proposes the following opposing hypotheses:

H1a: Enterprises' digital transformations can positively promote breakthrough green innovation.

H1b: Enterprises' digital transformations will inhibit breakthrough green innovation to a certain extent.

Data and Measures

Samples and Data Sources

This study uses China's A-share-listed companies from 2007 to 2019 as research samples, in which the enterprises' patent data is derived from the State Intellectual Property Office (SIPO), and the financial data is from *China Stock Market Accounting Research* (CSMAR). The sample is selected primarily due to the following considerations: First, China significantly adjusted its accounting standards in 2007. Second, the onset of the COVID-19 pandemic in 2020 may have impacted on enterprises' investment and innovation decisions. We maintained data consistency by establishing the study period after 2007 and before the onset of the COVID-19 pandemic. This paper's initial research samples exclude listed companies that have received special treatment (ST, ST*) and have missing major variables, such as enterprise size and management shareholding ratio. After this screening, 14,382 company-year observations were ultimately obtained, involving 2,246 listed companies. This paper avoids the influence of extreme values by indenting all continuous variables by up and down 1%.

Variables' Definition

Measuring breakthrough green innovation

The explained variable is breakthrough green innovation, which is obtained by referring to the practice of Byun et al. (2020) and using the technology similarities of enterprises' green patents as measurement. Whether an enterprise stays or deviates from a known field of research is determined by comparing the technological proximity between the patents applied by the enterprise in year t and the portfolio of patents held before year (t – 1). The formula is calculated as

$$TechProximityit = \frac{X_{i,t}X'_{i,t-1}}{(X_{i,t}X'_{i,t})^{0.5}(X_{i,t-1}X'_{i,t-1})^{0.5}} \quad (1)$$

where $X_{i,t}$ represents the patent portfolio applied by enterprise i in year t, and $X_{i,t-1}$ denotes the firm's proportion of patents in each patent classification up to year (t – 1). The larger the index, the greater the degree of homogeneity among enterprises' green patents; that is, enterprises are more inclined to incremental green innovation. In contrast, the smaller the enterprise's technological similarity index, the lesser the degree of homogeneity of the enterprise's green patent; that is, the enterprise is more inclined to breakthrough green innovation.

Notably, several zero values exist for the enterprise's number of green patents. Therefore, existing literature primarily adopts the logarithmic transformation method to solve the "right-skewed distributions" problem regarding the number of patents. According to Aihounton and Henningsen's (2021) suggestion, this paper adopts an inverse, hyperbolic sine transformation to replace the logarithmic transformation. The advantage of this method is that it can obtain regression results similar to the logarithmic transformation without any operation on the original variables. This can better overcome the problem of the explained variable being right-skewed. The formula is calculated as

$$arcsinh(z) = log(z + \sqrt{z^2 + 1}) \quad (2)$$

where z is the enterprise's number of green patent applications; the patent applications from enterprise i in year t are denoted as $X_{i,t}$ after the reverse hyperbolic sine transformation.

Measuring digital transformation

The explanatory variable is the enterprise's degree of digital transformation. This paper conducts a text analysis of the listed companies' annual reports to measure the enterprises' degree of digital transformation. Studies have proven that annual reports can best reflect an enterprise's strategic characteristics and future prospects, and to a large extent, reflect its business philosophy and consequent development path (Wu et al., 2021; Yuan et al., 2021). Therefore, it is both feasible and scientific to describe the applications' degree of digital technology based on word frequency statistics involving "digital technology" in the listed enterprises' annual reports (Song et al., 2022; Wu et al., 2021; Yuan et al., 2021).

We construct the firms' digital transformation indicator by following the method and steps presented by Wu et al. (2021) and Yuan et al. (2021), or specifically, by using the natural logarithm of the total number of the keywords from the digital technology application, plus one to measure the level of digital transformation. When generating a dictionary describing the enterprises' digital transformation, we considered the following topics, as these are typical terms representative of digital technologies: Big Data, cloud computing, blockchain, artificial intelligence, the Internet of Things, 5G, mobile Internet, virtual reality (i.e., VR), augmented reality (i.e., AR), deep learning, machine learning, digital twin, edge computing, and mobile payment. This paper took these digital technology terms as "seed" vocabularies, with the final selection of keywords referring to such relevant research as Wu et al. (2021) and existing authoritative research reports.[5] If the seed words and keywords with high degrees of correlation appear in an enterprise's annual report, then the enterprise used the digital technology in the current year. Simultaneously, relevant national digital economic policy-related documents and existing authoritative research reports from the China Academy of Information and Communications Technology (CAICT) and a Python crawler function were used to screen out 158 words related to the enterprises' digital transformation.

To further ensure that the selected keywords are representative, we ultimately retained 75 keywords that occurred more than or equal to 10 times in digital technology applications to obtain a dictionary describing the enterprises' digital transformation. The words that conformed to the digital technology application dictionary were searched and matched, and summary statistics performed. Finally, we calculated the proportion of the word frequency related to digital technology application accounts to the total number of words in the enterprise's annual report in the current year. This was used as a proxy variable to measure the enterprises' degree of digital transformation. It should be noted that this paper measures the enterprises' digital technology application level using a word frequency counting method, which may result in a 'right-biased' indicator. To address this limitation, the paper employs reverse hyperbolic sinusoidal transformation processing, referred to as Digtech.

Other control variables

The following control variables were used：1. The enterprise's scale (*Size*), as larger enterprises can obtain more green innovation resources; 2. The enterprise's age (*Age*), as the longer an enterprise has been established, the greater its inclination to innovate along an existing technological route; 3. The number of employees per hundred (*Employee*), as enterprises with richer human capital may be better at using internal and external resources for green innovation; 4. The asset-liability ratio (*Lev*), as enterprises with a low leverage ratio may improve their innovation ability through mergers and acquisitions; 5. The rate of assets (*Roa*), which can reflect the enterprise's performance to a certain extent, as the better the enterprise's performance, the more certain the company will have sufficient R&D funds; 6. The operating income growth rate (*Growth*), as the greater an enterprise's growth rate, the greater its growth potential, and it may promote higher-risk innovation activities; 7. The proportion of independent directors (*Indenp*), as Balsmeier et al. (2017) found that an independent board of directors would lead enterprises to narrow the scope of innovation to more familiar knowledge fields, thus avoiding exploring potential breakthrough innovations; 8. The management's shareholding ratio (*Share*) as the optimal contract theory posits that an equity incentive can best coordinate the interests of both management and shareholders, and encourage

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[5] Research reports referenced in this paper include: *China's Digital Economy Development White Paper*, *Cloud Computing White Paper*, *Trusted Artificial Intelligence White Paper*, *AI Core Technology Industry White Paper*, *Virtual (augmented) Reality White Paper*, *Blockchain White Paper*, *Big Data White Paper*, *Internet of Things White Paper*, and the *Industrial Internet Industry Economic Development Report*. These research reports are derived from the China Information and Communication Academy (CAICT).

management to make innovative decisions; and 9. The nature of the enterprise's ownership (*Govcon*), as state-owned enterprises also need to undertake certain political tasks, so their willingness to innovate may not be as high as that of private enterprises.

Variable Name	**Variable**	**Variable Definition**
Digital Transformation n	*Digtech*	Obtained through a text analysis method
Similarity of Green Innovation Technology	$TechProximity_{it}$	The degree of similarity between the green patent applied by enterprise *I* in year *t* and the patent applied in the previous year
Enterprise Scale	*Size*	Total enterprise assets
Enterprise Age	*Age*	The business' age of establishment
Number of Employees	*Employee*	The business' number of employees
Asset-Liability Ratio	*Lev*	The ratio of total liabilities to total assets
Rate of Assets	*Roa*	Rate of return on total assets
Increase in Rate of Business Revenue	*Growth*	The ratio of revenue growth to the prior year's total revenue
Proportion of Independent Directors	*Indenp*	Proportion of independent directors on the Board of Directors
Stock Ownership Incentive	*Share*	Level of managerial-share ownership
Ownership Nature	*Govcon*	A dummy variable scored as one if the enterprise is a state-owned enterprise, and zero otherwise

Table 1. Variable Definitions

Empirical Model

This paper uses a two-way fixed-effects model to estimate the impact of enterprises' digital transformation on green innovation strategy; the specific model is set as follows:

$$TechProximity_{it} = \alpha + \beta_1 Digtech_{i,t-1} + \beta_2 Controls_{i,t-1} + \lambda_t + \delta_i + \varepsilon_{it} \tag{3}$$

where the explained variable $TechProximity_{it}$ represents the green technology similarity of enterprise *i*; the greater the index, the greater the degrees of homogeneity between the enterprise's green patents, indicating that the enterprise's green innovation strategy is more inclined toward incremental green innovation. The explanatory variable $Digtech_{i,t-1}$ represents the digital technology application level of enterprise *i* in year (*t* – 1), which is constructed by text analyses with reference to practices by Yuan et al. (2021) and Wu et al. (2021). Considering that the possible reverse causality problem may interfere with the regression results, the core explanatory variables, and all control variables are lagged by one period. The coefficient β_1 denotes the impact of enterprises' digital transformation on the green technology similarity of concern in this paper. If the estimated coefficient is significantly less than zero, then the digital transformation promotes the enterprise's breakthrough green innovation. If the estimated coefficient is significantly positive, it indicates that digital transformation promotes the enterprise's incremental green innovation. Table 1 displays the set of control variables. Finally, λ_t and δ_i denote the year versus enterprise fixed effects, and ε is the random error term.

Table 2 lists the basic statistical characteristics of this paper's main variables. The average value of green patent technology similarity (*TechProximity*) among the listed manufacturing enterprises during the sample period is 0.16, and the maximum and minimum values are 1.00 and 0.00, respectively. Therefore, a significant gap exists in green innovation strategies among enterprises. The mean and standard deviation of enterprise digital transformation indicators are 0.99 and 1.20, respectively, demonstrating that the different enterprises' levels of digital transformation also greatly vary. The control variables' statistical characteristics are consistent with existing research.

Variable Symbol	Sample Size	Mean	Standard Deviation	Minimum	Median	Maximum
TechProximity	14,382	0.16	0.09	0.00	0.00	1.00
Digtech	14,382	0.99	1.20	0.00	0.69	6.17
Size	14,382	21.84	1.17	17.69	21.68	27.39
Age	14,382	2.75	0.37	0.69	2.77	3.95
Employee	14,382	7.66	1.17	2.07	6.34	12.44
Lev	14,382	0.39	0.20	0.05	0.38	0.87
Roa	14,382	0.05	0.19	-0.17	0.04	0.20
Growth	14,382	0.04	0.07	-0.15	0.04	0.23
Indep	14,382	0.37	0.05	0.33	0.33	0.57
Share	14,382	0.15	0.21	0.00	0.01	0.69
Govcon	14,382	0.35	0.48	0.00	0.00	1.00

Table 2. Variables' Basic Statistical Characteristics

Empirical Results and Analysis

Baseline Results

Table 3 reports the core test results of the relationship between the manufacturing enterprises' digital transformations and their green innovation mode.

	(1) *TechProximity*	(2) *TechProximity*
Digtech	0.0118***	0.0097**
	(0.0040)	(0.0040)
Size		0.0076
		(0.0110)
Age		0.0788
		(0.0571)
Employee		0.0171*
		(0.0088)
Lev		0.0054
		(0.0295)
Roa		0.2018**
		(0.0596)
Growth		-0.0120*
		(0.0062)
Indenp		-0.1508
		(0.0804)
Share		0.0202
		(0.0403)
Govcon		-0.0020
		(0.0191)
Constant	0.0434***	-0.2659*
	(0.0084)	(0.1436)
Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Observations	14,382	14,382
Within R^2	0.0439	0.0469

Table 3. Digital transformations' impact on the green innovation mode

Note: *, **, and *** indicate that the estimated results are significant at the 10%, 5%, and 1% levels, respectively. The estimation coefficients' heteroscedastic, robust standard errors are noted in parentheses. The following tables are the same.

In the benchmark regression, both firm- and time-fixed effects are controlled. In Column (2), after adding a series of control variables that may affect the green innovation output, the regression coefficient *Digtech* on green technology similarity (*TechProximity*) is 0.0097, and passes the 5% statistical significance test. The regression coefficient is positive, indicating that the source of the increasing number of green patents is mainly incremental green innovation, instead of the breakthrough green innovation of focus in this paper. From an economic perspective, every 1% increase in the enterprise's level of digital transformation increases its green patent applications' technical similarity by 0.97% relative to the mean. The impact of manufacturing digital transformation on green innovation models shows obvious technical similarities. Generally, the research results in Table 3 reveal that the digital transformation will inhibit breakthrough green innovation to a certain extent, initially confirming our Hypothesis H1b.

Endogeneity Problem

Reverse causality is an important source of possible endogeneity in this paper. Although the explanatory and control variables are lagged by one period in Model (3), the problem of reverse causality may still exist. Although enterprises' digital transformations significantly promote incremental green innovation, enterprises that prefer incremental innovation in their green innovation activities may be more inclined to applying digital technologies to search for similar technological resources to reduce innovation costs, thus engaging in low-quality green innovation that remains in the original technical field. This paper adopts an instrumental variable method to address these problems. Effective instrumental variables should meet two conditions: correlation and exogeneity. Specifically, this paper's instrumental variables should only indirectly affect enterprises' green innovation modes through enterprise-level digital transformations.

Based on these criteria, this paper uses the added value of digital technology application industries at the provincial level in China in 2007 as the instrumental variable[6] of enterprise-level digital transformations. This instrumental variable's validity is reflected in the following characteristics. First, the higher the added value of the digital technology application industry in the enterprise's province, the more developed the local digital technology application industry. It is beneficial for local enterprises to contact and apply digital technologies for earlier digital transformations to meet the relevant conditions. Second, this indicator is a historical instrumental variable. With the continuous changes and developments in digital technologies, it is difficult for the 2007 development level of the digital technology application industry to affect enterprises' current R&D investment and patent application decisions. Finally, because the historical digital technology application industry value-added involves cross-sectional data, it is unsuitable for the panel data structure. Therefore, this paper uses the interaction term of the added value of the digital technology application industry in each province in 2007 and the enterprise growth rate[7] of the national digital technology application industry in the previous year as an instrumental variable for the enterprise's digital technology application level.

Table 4 reports the instrumental variables' test results. Column (1) displays the first-stage estimation results. The instrumental variable coefficient is significantly positive at the 1% level. Specifically, the more developed the region's digital technology application industry, the higher the enterprises' level of digital technology applications, and the higher level of digital transformation of the enterprises, which parallels theoretical expectations. Simultaneously, the F-statistic from the first-stage regression is considerably greater than 10 and passes the weak instrumental variable test, indicating that the instrumental variable selected in this paper is appropriate. Column (2) demonstrates that the impact of enterprises' digital transformations on the green technology similarity is still significantly positive at the 5% level, confirming the robustness of this paper's benchmark results.

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[6] According to the definition from the National Bureau of Statistics, the digital technology application industry primarily includes software products, information and communication technology services, and information transmission service industries. The data is derived from the 2007 input-output table by province.

[7] This paper obtains the data for industrial- and commercially registered enterprises from 2007 to 2020 through the Ministry of Industry and Commerce's website, which includes the enterprise's name, type, registration location, registration time, and main business, among other characteristics. It also provides the annual growth rate of enterprises in the national digital technology application industry according to the sum of the national year.

	Digtech	*TechProximity*
IV	0.0097** (0.0003)	
Digtech		0.0155** (0.0992)
Control Variables	Yes	Yes
Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Observations	14,382	14,382
R^2	0.1261	0.0681
Weak instrumental variable Checks F-value	53.084*** (0.0000)	—

Table 4. Instrumental Variable Test

Note: The standard error for enterprise-level clustering is noted in parentheses. The control variables include the enterprise's size, age, number of employees, asset-liability ratio, net profit rate of total assets, growth rate of operating revenue, proportion of independent directors, equity incentive, and ownership nature.

Robustness Test

Eliminate the deviations in enterprises' disclosure information

This paper uses a machine-learning text analysis method to describe enterprises' digital transformation level by analyzing the information related to "digital technology" phrasing as disclosed in the listed companies' annual reports. However, Zhao et al. (2020) found that some listed companies tend to exaggerate the disclosure of Internet-related and other similar information in their annual reports to attract market attention. This paper employs the following processing method to decelerate the measurement error caused by exaggerated information disclosures in enterprises' annual reports: First, we refer to the Digital Transformation Research Database of Chinese-Listed Companies[8] jointly developed by CSMAR and the School of Business Administration at East China Normal University. In addition to a text-based analysis, the companies' historical data—such as their management's digital innovation performance, the construction of digital technology facilities, and the number of authorized digital invention patents—are incorporated into our evaluation system. To a certain extent, this alleviates the disadvantages of analyzing the introduction and application of digital technology in the enterprises' annual reports solely based on text.

Second, we reference practices by Song et al. (2022) and divide the two parts of the annual report into a "performance review" and "future outlook" given the frequency and timing of words related to the application of statistical digital technology. Among them, the "performance review" summarizes the previous year's work, which can better reflect the enterprise's actual level of digital technology applications. Therefore, the core explained variable is replaced by counting the word frequency related to the application of digital technologies in the "performance review" section. Columns (1) and (2) in Table 5 present the regression results of these tests. Comparing the benchmark regression results reveals that after considering the measurement error among the core explanatory variables, the conclusion is still significantly valid that manufacturing enterprises' digital transformations can promote their incremental green innovation.

[8] The CSMAR database of enterprises' digital transformations includes their strategic leadership, whether they are technology-driven, the organizational empowerment at the listed company-level, their digital achievements and applications, and medium and macro-level environmental support, and constructs an evaluation system for an enterprise digital transformation index.

Replace the explained variable

Referring to the method of Custódio et al. (2019), this paper uses the proportion of exploratory green patents to measure the degree of knowledge overlapping in enterprises' green innovation process, which is then used as a proxy variable for breakthrough green innovation. The measures are expressed as follows.

If more than 80% of the IPC4 patent classification numbers cited by a green patent and as applied by an enterprise in a certain year differ from those of the existing company's patent portfolio, the patent is considered to be exploratory. We calculate the proportion of exploratory patents in each year by considering two factors: the firm's own patents and patents cited in the firm's patent applications from the past five years. This demonstrates the enterprises' green patents applications' degree of deviation from the original technical field every year, which measures breakthrough green innovation and is denoted as *ExploratoryRatio80*. Similarly, the proportion of exploitative green patents is used as the proxy variable for incremental innovation, denoted as *ExploitativeRatio80*. Columns (3) and (4) in Table 5 display the estimated results after replacing the explained variables. While the regression coefficient of *Digtech* to *ExploitativeRatio80* is significantly positive, the regression result of *ExploratoryRatio80* is insignificant, indicating that this paper's benchmark result is robust.

Consider the problem of omitted variables

The previous regression controlled for year- and enterprise-level fixed effects, but other factors may be difficult to observe that relate to both enterprises' digital transformations and green innovation strategies. For example, when the enterprise's region is impacted by a certain green technology innovation policy, enterprises that originally lacked sufficient green technology resources or are in low-innovation industries will be able to use digital technologies in their digital transformation processes due to the low opportunity cost. Therefore, this paper retains the enterprise-level fixed effects. Columns (5) and (6) in Table 5 successively add the fixed effects of province × year and industry × year to control for the influence of unobservable regional- and industrial-level factors that change over time on enterprises' green innovation strategies. The results reveal that no significant change occurs in the size and significance of the regression coefficient for the impact of enterprises' digital transformation on green technology similarity. Therefore, it can be considered that this paper's basic conclusion is less affected by the omitted variables.

	(1)	(2)	(3)	(4)	(5)	(6)
	TechProximity		*ExploitativeRatio80*	*ExploratoryRatio80*	*TechProximity*	
Digtech	0.0014**	0.0045***	0.0063**	0.0048	0.0025***	0.0026***
	(0.0008)	(0.0011)	(0.0029)	(0.0048)	(0.0009)	(0.0009)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	No	No
Province × Year F.E	No	No	No	No	Yes	Yes
Industry × Year F.E.	No	No	No	No	No	Yes
Observations	14,382	14,382	14,382	14,382	14,382	14,382
Within R^2	0.0515	0.0553	0.1542	0.1542	0.0932	0.1031

Table 5. Robustness Test

Heterogeneity Analysis

Differentiate industry types

Currently, digital transformation has become a part of enterprises' strategic development, but significant differences exist in the digital infrastructure investments and digital resource management capabilities in different industries. In particular, the green innovation models for enterprises in different industries may be affected differently by digital transformation. For example, technology-intensive manufacturing industries—such as the pharmaceutical, electronics, and information technology industries, which are oriented toward cutting-edge technological innovation—exhibit a higher demand of digital technology applications to improve the efficiency of green innovations under green development and corresponding environmental protection requirements. Although labor- and capital-intensive industries, such as food manufacturing, construction, petrochemicals, and metals, also need to adopt digital technologies to improve their green production efficiency, they generally exhibit lower levels of breakthrough innovation ability and less willingness to pursue green innovations compared to technology-intensive industries. This is evidenced by [provide specific evidence or examples.

This paper referred to Lu and Dang's (2014) research and the criteria from the National Economic Industry Classification to divide the enterprises' industry types into three groups: labor-, capital-, and technology-intensive. We then performed a sub-sample regression; Columns (1) through (3) in Table 6 present the regression results, which are consistent with expectations. Specifically, digital transformations have a significant effect on the breakthrough green innovation of enterprises in technology-intensive industries, but the impact on labor- and capital-intensive industries is small and statistically insignificant. This is because technology-intensive industries more closely align with developments in the digital technology sector, and these firms are more willing to apply their digital transformation results to green innovation activities.

	Explained Variable: *TechProximity*				
	Industry Type			Market Competition	
	Labor-intensive (1)	Capital-intensive (2)	Technology-intensive (3)	High (4)	Low (5)
Digtech	0.0001 (0.0017)	0.0014 (0.0017)	-0.0032*** (0.0012)	-0.0125*** (0.0059)	0.0023 (0.0062)
Control variables	Yes	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Observations	3,167	3,885	7,330	6,286	6,279
Within R^2	0.0607	0.0514	0.0595	0.0591	0.0256

Table 6. Heterogeneity Analysis

Differentiate external market structure

In reality, the degree of market competition has prominently impacted enterprises' internal management decisions, and the market competition and innovation relationships are also fundamental issues in developing anti-monopoly policies. In recent years, the market concentration trends brought about by a developing digital economy and the strong monopoly power of large digital-platform enterprises have raised concerns that the market concentration will hinder innovation (Tang et al., 2022). Further, Baker et al. (2021) used microenterprise data from the United States to empirically determine that as large firms occupy an increasingly high market share, the market's high concentration will lead to a clear downward trend in the number of innovations in the United States' economy. Conversely, more competitive industries will create clearer incentives for enterprises to adopt certain offensive or defensive competitive behaviors to obtain or maintain a competitive advantage (Chen and Wang, 2015).

This paper refers to the method developed by Tang et al. (2022) and uses the Lerner index to measure enterprises' degree of market competition. We incorporated the Lerner index to divide our sample enterprises into those with high or low market competition according to the median Lerner index of all the sample enterprises in the different observation years. Columns (4) and (5) in Table 6 present the empirical results. When in a market with a small Lerner index—or that with a higher degree of market competition—enterprises' digital transformations promote breakthrough green innovation at a 5% significance level. Therefore, enterprises in highly competitive markets will be more susceptible to incentives from creating internal competitive advantage as well as external government regulations. In terms of green transformations, these enterprises will be more motivated to use digital transformation results to engage in breakthrough green innovations that deviate from existing technical knowledge.

Discussion and Conclusions

In the digital economy era, digital technologies as primarily represented by Big Data and cloud computing, among others, continue to evolve. With the deep integration of emerging digital technologies and green and low-carbon industries, the coordinated development of dualization has become a national strategy in China. Digital transformations have become a new engine to promote enterprises' green innovation, especially among manufacturing enterprises, as the main focus of green innovation involves undertaking important tasks toward green and high-quality development. Given this context, this paper first proposes promoting and inhibiting enterprises' digital transformations toward breakthrough innovations that reflect high-quality green development from the perspectives of technical resource supplementation, information overload, and resource extrusion. We then used panel data from listed manufacturing enterprises from 2007 to 2019 to empirically analyze digital transformations' impacts on enterprises' breakthrough green innovation.

This paper's main findings include the following: (1) Digital transformations in the manufacturing industry have significantly promoted green innovation among enterprises with high degrees of technological similarity. The current increase in the number of green innovations is not primarily comprised of highly efficient or high-quality breakthrough innovations. (2) Significant differences exist in the green innovation models of enterprises involved in digital transformations within the manufacturing industry. Enterprises in technology-intensive industries under strong market competition have more apparent upgrades to the green innovation model brought by digital transformations, and these upgrades manifest as a significant promotion of breakthrough green innovation among these enterprises.

This research's conclusions are highly significant in fostering a deeper understanding of the actual effects of the manufacturing industry's digital transformation under China's current green development phase. These results can be employed in reasonably formulating green development plans from the perspective of internal enterprise and external government regulations and promoting the green transformation and upgrading of China's more traditional manufacturing industry. We offer the following points to consider as a result of our research:

First, green transformations have become an inevitable requirement for high-quality development in the manufacturing industry, and digitalization, in particular, provides a beneficial conduit for such transformations. Thus, enterprises should employ digital technology applications to achieve long-term green development and engage in more novel technologies, such as those involving breakthrough green innovations. Further, enterprises can embed digital technologies and platforms—such as industrial robots, 3D printing, and an industrial Internet—into traditional manufacturing enterprises' production processes according to their own needs. This will ultimately promote green transformations among these digitally empowered enterprises. Simultaneously, the government can guide and focus on the breadth and depth of relevant policy support to help solve practical dilemmas in difficult data collection processes. In their involvement in the transitioning and application of relevant data collection in manufacturing enterprises' production processes, the government can further promote the integration of both informatization and industrialization.

Second, the implementation and supervision of green innovation must also fully consider the heterogeneous characteristics of both enterprises and industries. Policy support must be provided according to the green innovation characteristics and needs of different types of enterprises to strengthen the degree of green technology protections for technology-intensive enterprises and to continuously optimize the financing environment for enterprises with high green innovation investments. For example, the government can strengthen green credit support to alleviate the resource crowding problem caused by digitalization and encourage high-quality breakthrough green innovations. Moreover, the formulation of relevant industrial policies should consider the innovation resources for enterprises with high degrees of market competition and timely supplement the external resources needed by enterprises in the green innovation process for a fair and just green innovation environment. Thus, this study aims to promote green, sustainable enterprise development and encourage them to build a long-term green competitive advantage through breakthrough innovations.

This work offers the following theoretical contributions. First, this study enriches the research on breakthrough innovation theory. Many studies have discussed the factors influencing breakthrough innovation, but few have considered the impacts of digital transformations on firms' breakthrough innovation in the digital economy era. Second, this study extends the relevant research on corporate digital transformations and green innovation. While existing literature has discovered that digital transformations can increase enterprises' number of green innovations, it has not investigated whether the cause of the increase is incremental or breakthrough green innovations based on novel green technologies. In terms of practical significance, given the rapidly increasing quantity of green innovations in China but their low quality, it is of great practical significance to discuss whether enterprises' digital transformations can promote breakthrough green innovation to improve the quality of green innovations in China and achieve a national goal of becoming an innovation powerhouse.

However, this study also has the following deficiencies: First, due to the availability of data, this study did not separately examine the impacts of specific manufacturing production and operations on firms' green innovations. As production is theoretically the core business of manufacturing, and enterprises with strong digital production capabilities are more likely to use digital transformations to add data and technical resources in time to create green innovations with novel technologies, these enterprises will be more willing to participate in green innovations. Future studies can consider this to distinguish the internal links from manufacturing digital transformations and explore what types of business process digitalization can help facilitate enterprises' breakthrough green innovation decisions. Second, enterprises' green innovation decisions may be influenced by their external environment and internal characteristics. Therefore, future research should focus on the positive factors regulating the manufacturing industry's digital transformations and breakthrough green innovations.

References

Acemoglu, Daron, Ufuk A., Murat A.C. (2022). Radical and Incremental Innovation: The Roles of Firms, Managers, and Innovators. *American Economic Journal: Macroeconomics, 14 (3),*199-249.

Aghion P., Boneva L., Breckenfelder J.H., Laeven L., Olovsson C., Popov A., & Rancoita E. (2022). Financial Markets and Green Innovation. *SSRN Electronic Journal*.2686.

Aihounton G.B.D. & Henningsen A. (2021). Units of measurement and the inverse hyperbolic sine transformation. *The Econometrics Journal, 24(2), 334-351*.

Balsmeier B., Fleming L. & Manso G. (2017). Independent boards and innovation. *Journal of Financial Economics, 123*(3),536-557.

Baker P. M. A., Gaspard H., & Zhu J. A. (2021). Industry 4.0/Digitalization and networks of innovation in the North American regional context. *European Planning Studies,* 1–15.

Byun S. K., Oh J. M. & Xia H. (2020). Incremental vs. breakthrough innovation: The role of technology spillovers. *Management Science*, Articles in Advance, 1–24.

Capponi G., Martinelli A., & Nuvolari A. (2022). Breakthrough innovations and where to find them. *Research Policy*, 51(1),104376.

Chen Z.B. & Wang S.Y. (2015). Research on the Impact of Product Market Competition on Enterprise Cash Flow Risk: Based on the Dual Considerations of Industry Competition and Enterprise Competitive Position. *China Industrial Economics (03),*96-108. (In Chinese).

Chin T., Shi Y., Singh S.K., Agbanyo G.K. & Ferraris A. (2022). Leveraging blockchain technology for green innovation in ecosystem-based business models: A dynamic capability of values appropriation. *Technological Forecasting and Social Change*, 183, 121908.

Custódio C., Ferreira M. A. & Matos P. (2019). Do general managerial skills spur innovation? *Management Science*, 65(2), 459-476.

Dou Q. & Gao X. (2022). The double-edged role of the digital economy in firm green innovation: micro-evidence from Chinese manufacturing industry. *Environmental Science and Pollution Research, 29(45)*, 67856-67874.

El-Kassar A. N. & Singh S. K. (2019). Green Innovation and Organizational Performance: The Influence of Big Data and The Moderating Role of Management Commitment and HR Practices. *Technological Forecasting and Social Change, 144*(7),483-498.

Enrique D.V., Lerman L.V., Sousa P.R., Benitez G.B., Santos F.M.B.C. & Frank A.G., (2022). Being digital and flexible to navigate the storm: How digital transformation enhances supply chain flexibility in turbulent environments. *International Journal of Production Economics.250*,108668.

Forés B. & Camisón C. (2016). Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? *Journal of business research, 69*(2),831-848.

Feng H., Wang F., Song G. & Liu L. (2022). Digital Transformation on Enterprise Green Innovation: Effect and Transmission Mechanism. *International Journal of Environmental Research and Public Health (19),*17.

Gu H.F. & Gao S.W. (2022). Study on the Influence of Digital Finance Development to Enterprise Green Innovation. *Journal of Statistics and Information*, 37(11),77-93.

Jiang S., Li Y. & You N. (2023). Corporate digitalization, application modes, and green growth: Evidence from the innovation of Chinese listed companies. *Frontiers in Environmental Science (10)*, 1103540.

Kaplan S. & Vakili K. (2014). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal, 36*(10), 1435–1457.

Lanzolla G., Pesce D. & Tucci, C. L. (2021). The digital transformation of search and recombination in the innovation function: Tensions and an integrative framework. Journal of Product Innovation Management, 38(1), 90-113.

Li B.Z. & Zeng J.W. (2019). The Influence of Knowledge Inertia on Ambidexterity Innovation. Studies in Science of Science, 37(04),750-759. (In Chinese).

Li S.W., Luo J.L. & Ge Y.Q. (2021). Effects of Big Data Analysis Capability on Breakthrough Product Innovation. Journal of Management Science (02),3-15. (In Chinese).

Liu X., Liu F. & Ren X. (2023). Firms? digitalization in manufacturing and the structure and direction of green innovation. *Journal of Environmental Management (335), 117525.*

Lu T. & Dang Y. (2014). Corporate Governance and Technology Innovation: A Comparison by Industry. *Economic Research* (06),115-128. (In Chinese).

Manso G.（2011）. Motivating innovation. *The Journal of Finance, 66*(5), 1823-1860.

Mubarak M.F., Tiwari S., Petraite M., Mubarik, M. & Raja Mohd Rasi R.Z. (2021). How Industry 4.0 technologies and open innovation can improve green innovation performance? *Management of Environmental Quality: An International Journal. 1477-7835*

Nambisan S., Wright M. & Feldman M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy, 48*(8): 103773.

Nordhaus W. (2021). The Double Externality of Green Innovation. In The Spirit of Green: The Economics of Collisions and Contagions in a Crowded World, 204-224.

Shen M.H. & Tan W.J. (2022). Digitalization and Enterprise Green Innovation Performance: Dual Effect Identification Based on Increment and Quality Improvement. *Southern Economy (09)*,118-138. (In Chinese).

Shen K.R., Lin J.W. & Fu Y.H. (2023). Network Infrastructure Construction, Information Availability and Enterprise Innovation Boundaries. *China Industrial Economics (01)*, 57-75.

Song D.Y., Zhu W.B & Ding H. (2022). Can enterprise digitalization promote green technology innovation? Based on the investigation of listed companies in heavy polluting industries. *Journal of Finance and Economics (04)*,34-48. (In Chinese).

Sun Y.B. & Sun H. (2021). Green Innovation Strategy and Ambidextrous Green Innovation: The Mediating Effects of Green Supply Chain Integration Additional contact information. *Sustainability,13(9), 1-20.*

Tao F., Zhao J.Y. & Zhou H. (2021). Does Environmental Regulation Achieve "Incremental Quality Improvement" in Green Technology Innovation: Evidence from Environmental Target Accountability. *China Industrial Economics (02)*,136-154. (In Chinese).

Tang C., Xu Y.Y., Hao Y., Wu H.T. & Xue Y. (2021). What is the role of telecommunications infrastructure construction in green technology innovation? A firm-level analysis for China. *Energy Economics*,103,105576.
Tang Y.J., Wang Y. & Tang C.H. (2022). Digital economy, market structure and innovation performance. *China Industrial Economics (10)*,62-80. (In Chinese).
Vial G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144.
Waqas M., Hong gang X. & Ahmad N. (2021). Big Data Analytics as a Roadmap towards Green Innovation, Competitive Advantage and Environmental Performance. *Journal of Cleaner Production*, 323(10), 128998.
Wang F.Z., Liu X.L., Zhang L.& Cheng W.H. (2022). Does digitalization promote the innovation of green technology in resource-based enterprises? *Science of Science (02)*, 332-344. (In Chinese).
Wang J., Xue Y., Sun X., & Yang J. (2019). Green learning orientation, green knowledge acquisition and ambidextrous green innovation. *Journal of Cleaner Production*, 119475.
Wang X., Zhang X.N. & Niu Y.W. (2022). "Data-driven" and "capability curse": the strategic paradox of enterprise digital transformation under the orientation of green innovation strategy upgrading. *Research and Development Management (04)*,51-65. (In Chinese).
Westerman G. & Bonnet D.C. (2015). Revamping your business through digital transformation. *MIT Sloan Management Review,* 26, 10-13.
Wu L., Hitt L. & Lou B. (2020), Data Analytics, Innovation, and Firm Productivity. *Management Science,* 66(5),2017-2039.
Wu F., Hu H.Z., Lin H.Y. & Ren X.Y. (2021). Corporate Digital Transformation and Capital Market Performance: Empirical Evidence from Equity Liquidity. *Management World* (07), 130-144+10. (In Chinese).
Xie X.M. & Han Y.H. (2022). How can local manufacturing enterprises achieve "gorgeous transformation" in green innovation? A multi-case study based on the basic view of attention. *Management World* (03), 76-106. (In Chinese).
Yang S.L., Chen N. & Li L. (2022). Digital Transformation and Enterprise Innovation Efficiency—Empirical Evidence from Chinese Manufacturing Listed Companies. *Operations Research and Management Science, 31(05),169-176. (In Chinese).*
Yang H., Li L. & Liu Y. (2022). The effect of manufacturing intelligence on green innovation performance in China. *Technological Forecasting and Social Change, 178, 121569.*
Yi L.X., Wu F. & Chang X. (2021). Enterprise Digital Transformation Process and Main Business Performance: Empirical Evidence from the Text Recognition of Annual Reports of Listed Companies in China. *Modern Finance and Economics (Journal of Tianjin University of Finance and Economics (10),24-38. (In Chinese).*
Yuan C., Xiao T.S., Geng C.X. & Sheng Y. (2021). Digital Transformation and Enterprise Division of Labor: Specialization or Vertical Integration. *China Industrial Economics (09)*,137-155. (In Chinese).
Zhao C.Y. (2021). Digital Development and Servitization: Empirical Evidence from Manufacturing Companies. *Nankai Business Review,24(02),149-163.* (In Chinese).
Zhao J., Chen S.H. & Cao W. (2020). "Internet+" Information Disclosure: Substantive Statement or Strategic Hype: Based on Evidence of Stock Price Crash Risk. *China Industrial Economics (03)*,174-192. (In Chinese).
Zhang Q., Yang M., & Lv S. (2022). Corporate Digital Transformation and Green Innovation: A Quasi-Natural Experiment from Integration of Informatization and Industrialization in China. *International Journal of Environmental Research and Public Health*, 19(20), 13606.
Zhuang Z.Y., Jia H.J. & Xiao C.Z. (2020). Breakthrough Innovation Research Progress. *Economic Dynamics* (09), 145-160. (In Chinese).