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IS DIGITAL TECHNOLOGY INNOVATION A PANACEA FOR CARBON REDUCTION?

Zhengning PU[✉], Yu QIAN, Ruiheng LIU

School of Economics and Management, Southeast University, Nanjing, Jiangsu 210000, China

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Abstract. This paper analyses the impact of digital technological innovation on the carbon emission intensity of enterprises and conducts an empirical test based on the data of listed enterprises in China from 2009 to 2021. The study finds that (1) digital technological innovation can significantly reduce carbon emission intensity. (2) Enterprises' digital attention and investment can significantly increase their operating income but not reduce carbon emissions. Digital technology patents can significantly reduce carbon emissions in the short term. In the long run, even new digital technologies will have a carbon rebound effect once they are deployed on a large scale. Therefore, digital technology innovation is still challenging in the long run to realize the synergy effect of "increasing production and reducing carbon." (3) Mechanism tests show that digital technology innovation can reduce carbon intensity by improving operational efficiency, promoting cleaner production, and improving human capital. (4) If the government pays moderate attention to digital development, digital technological innovation by enterprises can significantly reduce carbon intensity. Meanwhile, this effect is more significant in regions with higher levels of intellectual property protection. Digital technology innovation can significantly reduce carbon intensity for mature, high-tech, and technology-intensive enterprises.

Keywords: digital technological innovation; carbon intensity; income growth; carbon reduction; rebound effect.

JEL Classification: O33, Q55, Q56.

[✉]Corresponding author. E-mail: ***puzhengning@seu.edu.cn***

1. Introduction

Global development urgently needs to balance economic growth and environmental protection. The COVID-19 pandemic has led to a short-term decline in global carbon emissions, with global CO2 emissions falling by 5.6% in 2020 compared with 2019 (IEA, 2021). However, as the economy recovers, carbon emissions from energy consumption quickly returned to 2019 levels. In particular, China's share of global carbon emissions is much higher than its share of GDP. In 2021, China's GDP accounted for only 18.37% of global GDP, but its share of carbon emissions was 30.89% (BP, 2022). China still has a long way to go to meet its "carbon neutral" target. As a developing country in transition, realizing the synergy between carbon emission reduction and output growth has become a major challenge for policymakers (S. Zhang et al., 2022).

With the advent of Industry 4.0 era, digital technologies such as artificial intelligence, Internet of Things, and virtual reality have increasingly become important factors affecting global economic production and ecological environment (Awan et al., 2022). Previous studies have shown that digital technology improves work efficiency and unlocks human potential, which can realize the optimal allocation of resources, thereby enhancing enterprise performance and manufacturing growth potential (Graetz & Michaels, 2018; Peng & Tao, 2022). Digital technology innovation (DTI)[1] can help drive the production of final goods and long-term economic growth (Cong et al., 2021). DTI and digital transformation have become inevitable to achieve sustainable development in the post-epidemic era (Saia, 2023). According to research data from Accenture, digital investment by leading Chinese companies has led to an 11% improvement in business performance, and nearly 60% of companies said they would increase their digital asset in the next 1–2 years (Accenture, 2022).

However, the massive use of digital technology has also brought concerns about global carbon emissions. Regarding carbon emission reduction, DTI can theoretically provide an impetus for carbon emission reduction by improving governance and energy efficiency (Liu et al., 2022b; Wang et al., 2021). However, it has to be acknowledged that the development and operation of infrastructure such as artificial intelligence, blockchain, and data centers requires a lot of energy-intensive infrastructure (Bianchini et al., 2023), which may contribute to more carbon emissions (Pu & Fei, 2022). At the same time, the innovation and use of new technologies may also lead to a "rebound effect" (Wang et al., 2023), which will also lead to the growth of carbon emissions (Sadorsky, 2012).

The disruptive impact of DTI on firms' production processes, product types, business models, and user experience has received much attention (Ciarli et al., 2021). However, most of the existing research focuses on the fields of digital transformation and digital economy (Ma & Zhu, 2022; Shang et al., 2023). There is little literature that integrates DTI, economic production, and carbon emissions into a single research framework. In addition, much of the existing literature uses digital word frequencies in corporate annual reports to study the impact of digital transformation (Shang et al., 2023), which can lead to biased estimates of the actual impact of digital technologies (Lu & Li, 2024). Because, this is ultimately just a development goal or a publicity slogan of companies, and it is still difficult to say how much actual impact it can have on production and carbon emissions. At the corporate level in particular, the evidence on whether DTI can increase production without increasing carbon is still patchy. The mechanism and effect of enterprise DTI on economy and carbon emission reduction is still unclear, and it is still a research gap.

Digital technologies and data elements are increasingly integrated into production, circulation, exchange and distribution. The dynamics and paradigm of economic production are undergoing a revolutionary shift, with dramatic implications for business production and carbon emissions. So can DTI reduce corporate carbon intensity? How does it affect the actual production of enterprises? Can it increase output without increasing carbon emissions? When enterprises face different internal and external environments, what kind of difference does this impact have? These are the main problems studied in this paper. As a consequence, there are three main objectives of this study. First, based on enterprise micro-data, the degree of enterprise DTI is systematically measured from three aspects: DTI attention, DTI input and

[1] Abbreviation: Digital technology innovation (DTI).

DTI output (patent). The second is to explain how DTI affects the carbon emission intensity of enterprises. The third is to empirically examine the comprehensive impact and heterogeneity of DTI on enterprise output and carbon emissions. A summary is given in Figure 1.

This paper can make the following three marginal contributions. (1) It enriches research on the impact of DTI on firms. This paper provides new insights into the effects and mechanisms by which DTI affects the carbon emission intensity of firms. To the best of our knowledge, there is still a gap in studying the impact of DTI on carbon emission intensity at the firm level. Our study differs from the existing literature investigating the digital economy's and digital transformation's impact on carbon emissions (Shang et al., 2023; W. Zhang et al., 2022). We focus on assessing the economic and environmental impacts of DTI and its processes for firms. (2) Improve micro-measurement research on DTI. Although the literature has measured DTI using digital patents and conducted empirical studies (Liu et al., 2023), this measure fails to reflect the process characteristics of DTI. This paper innovatively starts from the process and outcome of DTI. It constructs measurement indexes of enterprise DTI, including digital innovation attention, digital innovation input, and digital innovation outcome (patent), which overcomes the shortcomings of the existing literature on measuring DTI. (3) The impact and extent of DTI on firms' carbon intensity are empirically investigated, and exogenous instrumental variables and policy shocks mitigate possible endogeneity. Heterogeneity is analyzed at different levels, such as the external environment and internal conditions of firms, providing new insights for firms to formulate DTI strategies and for governments to design digital

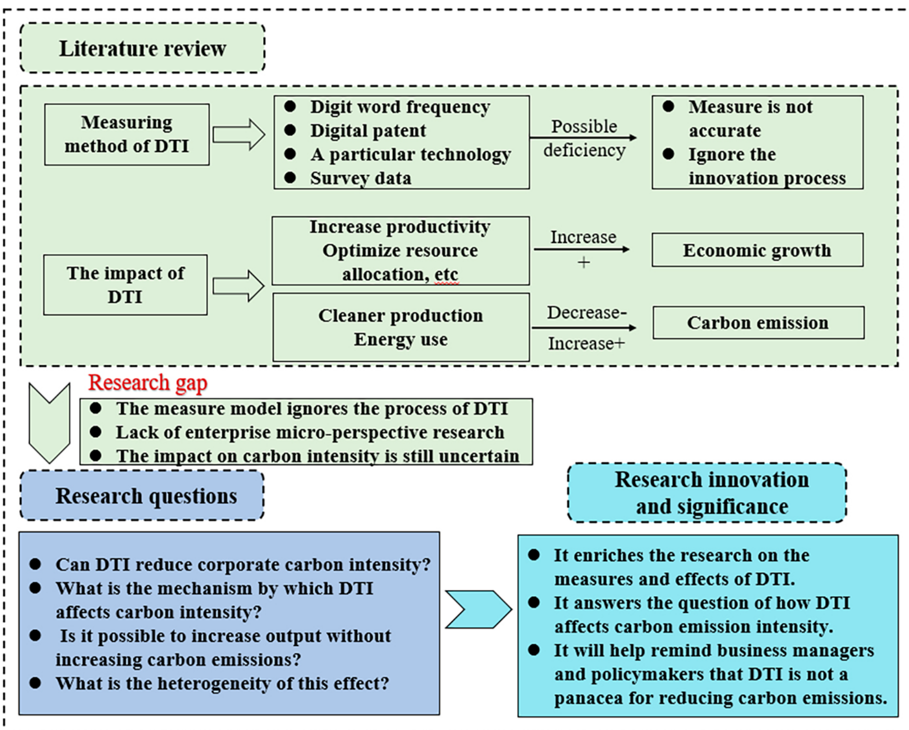

Figure 1. Research frame diagram

economy policy systems.

The rest of the paper is structured as follows: Section 2 is a literature review. Section 3 is the theoretical analysis of the impact of DTI on carbon emission intensity. Section 4 presents the research design. Section 5 discusses the empirical results. The last section is the conclusion and policy recommendations.

2. Literature review

2.1. Connotation and measurement of DTI

Yoo et al. (2010) defined the connotation of DTI earlier, believing that DTI is an innovation process of recombining digital components and physical components based on digital technology to produce new products, services, and business models. Woodard et al. (2013) argued that DTI improves existing outcomes or creates new products through digital technology. Digital technology refers to information, computing, communication, and connectivity technologies and their combinations, including technologies such as artificial intelligence, big data, and blockchain (Urbinati et al., 2020). Markus and Nan (2020) argued that DTI includes both the process and the outcome of innovation: the process is the recombination of social resources based on digital technologies, and innovation development is the introduction of new digital technologies, products, processes, or business models. Therefore, all new digital technologies can be traced back to some previous digital technology or combination of technologies (Chan et al., 2019). Digital technologies are both the foundation and one of the outcomes that drive DTI (Ciriello et al., 2018). For example, smartphones combine various digital technologies, such as ICT, electronic payment, and information storage (Chang et al., 2009).

There are three main ways to measure DTI. One is to measure the level of DTI by identifying firms' digital patents (Liu et al., 2023). Huang et al. (2023) used firms' digital patent data to study the impact of DTI on firm performance. Second, digital innovation is measured using a specific digital technology. For example, ICT technology is used as a proxy variable for DTI (Usai et al., 2021), and DTI is measured by technological innovation in the information industry (Wang et al., 2021). Third, the DTI of firms is measured by questionnaires (Khin & Ho, 2018).

Most of the various definitions of DTI emphasize the following key points: based on digital technologies, a combination of various digital technologies, an innovation process, and the generation of innovations such as new technologies, products, or business models (Hund et al., 2021). In contrast, most measures of DTI are based on digital patents, which do not reflect the process of DTI.

2.2. Impact of DTI on carbon emissions

The existing research on DTI and carbon emissions has two main points of view. One is that DTI can reduce carbon emissions. Wang et al. (2021) used the information technology industry in 50 countries as an example, and the study concluded that DTI will increase the intensity of local carbon emissions. Still, its spillover effect can strengthen upstream and downstream industries, thus reducing carbon intensity. Liu et al. (2022b) also concluded that DTI can promote carbon emission reduction and have a spillover effect on carbon emission reduction in neighboring countries. Adopting digital technology has become a necessary pathway to achieving net-zero carbon emissions (Yadav et al., 2023). As a type of digital economy, the sharing economy has also shown a significant impact on mitigating carbon emissions (Gu, 2022). Shen et al. (2023) used industrial robots as a manifestation of digital technology. They concluded the development of digital technology can help reduce carbon emissions, but the impact on high carbon emission areas is weak. Wang et al. (2023) concluded that using industrial robots lowers carbon emissions but also leads to an energy rebound effect that partially offsets the carbon reduction capacity of industrial robots.

Second, there is a non-linear relationship between DTI and carbon emissions. Low levels of digitalization increase carbon emissions, while high levels can improve management efficiency and reduce carbon emissions (Saia, 2023). At the provincial level in China, DTI reduces carbon intensity and has an inverted "U" curve on total carbon emissions (Z. Yang et al., 2022). Similarly, the application of digital technology in industry, government management, daily life, and cultural development will initially increase carbon emissions, but with growing digitalization, it will eventually reduce carbon emissions (Zheng et al., 2023).

In summary, many existing studies on the connotation and impact of DTI have laid the foundation for this paper. However, in terms of measurement, the existing literature mostly ignores the process characteristics of DTI. Studies on DTI and carbon emissions mainly focus on digital transformation or the impact of a specific digital technology (e.g., industrial robotics, artificial intelligence, ICT technology) on carbon emissions, which may underestimate the environmental benefits of DTI. The few studies that have examined the carbon reduction effects of DTI have also focused on the macro level, such as national, regional, or urban, and have reached relatively inconsistent conclusions. In particular, at the micro-enterprise level, the systematic study of the impact of DTI on carbon emission intensity is still rare. To fill this research gap, this paper measures the DTI of enterprises from the three aspects of digital innovation attention, digital innovation input and output, and empirically examines its economic and environmental impacts.

3. Mechanism analysis and research hypothesis

DTI is characterized by creative destruction and has already significantly impacted all aspects of business production, management, operations, and products (Chan et al., 2019). This paper analyses the effects of DTI on business carbon intensity from the perspectives of operational efficiency, clean production, and human capital enhancement.

3.1. Enhancement of operational efficiency

DTI is the process of reorganizing various digital technologies and creating new technologies. The process of DTI can optimize the organizational management and production process of enterprises and achieve more flexible production management. This can improve the efficiency of business operations, increase the output per unit of input factors, and thus reduce carbon intensity.

On the one hand, digital technologies such as AI, blockchain, and virtual reality have a disruptive impact on the management and operation of business organizations (Hilb, 2020).

DTI is combinatorial, self-growing, and replicable, blurring the boundaries between corporate departments, supply chains, customers, and even products and helping to enhance communication and collaboration among different stakeholders (Yoo et al., 2010). As a result, the division of labor has changed from a pyramidal structure to a flattened, networked, and collaborative organization. The flattened and networked organizational structure can be user-centered, achieving good communication and coordination between business processes, improving operational efficiency, and increasing enterprise output (Lee & Yang, 2014). Furthermore, DTI can enhance data collection and processing capabilities, which is conducive to improving the efficiency of data and information transfer, reducing communication costs, and accelerating the speed of resource integration. Various types of data and information, such as R&D, production, customer feedback, etc., are integrated through digital technology and used in enterprise development to help enterprises manage, control, and optimize business processes promptly and improve operational efficiency. The optimization of organizational management and operational processes can effectively improve resource efficiency and reduce carbon intensity (Fernando & Hor, 2017).

On the other hand, the DTI optimizes production processes. Many novel DTIs are essential to optimize production processes, promote resource recycling, and improve environmental sustainability (Ranta et al., 2021). Digital technologies like industrial robots and AI have been developed and used in business production. These digital technologies provide a platform that enables real-time connectivity and effective interaction between products and consumers, upstream and downstream manufacturers. The allocation of materials, labor, capital, and other factors in R&D and production is continuously and dynamically optimized, thus improving the enterprise's resource allocation efficiency and energy efficiency (Li et al., 2023). The optimization of the production process not only enhances resource allocation efficiency but also reduces the time from R&D, production, sales, and delivery, improves product satisfaction,n and increases customer stickiness (Un & Asakawa, 2015). In addition, the replicability of DTI reduces the marginal cost of production. It can even be replicated at zero cost, significantly increasing firm productivity and output per unit of factor input. It has been shown that DTIs that drive the optimization of production processes lead to better firm performance (Khin & Ho, 2018) and carbon reduction capabilities (Wang et al., 2023). This leads to Hypothesis 1:

H1: *The DTI reduces carbon intensity by improving the efficiency of business operations.*

3.2. Promoting cleaner production

The DTI is crucial for cleaner production because it can promote changes in the technological structure of society, make new technologies cleaner and more energy efficient, and promote carbon reduction in business production and sales (Mäkitie et al., 2023).

In terms of energy use, DTI can improve energy efficiency and promote the use of clean energy. Digital technologies can help companies better track and manage the use and production of renewable energy. Through smart grids, distributed energy management, and other digital technologies, companies can reduce dependence on traditional energy sources, integrate renewable energy into the production process orderly, and reduce carbon emissions from traditional energy use (Ghenai et al., 2022). Digital technology can also help companies reduce their dependence on traditional energy sources and reduce their carbon emissions. At the same time, digital technology can also help companies identify and select the optimal energy use scenarios to achieve efficient energy use. Through digital monitoring and control systems, companies can monitor and adjust energy consumption in real-time to reduce unnecessary energy waste. As a result, cleaner and more efficient energy use can be achieved, and the carbon emission intensity of enterprises can be reduced.

DTI provides enterprises with more innovative and greener production methods regarding production and operation. DTI can monitor and manage energy consumption and carbon emissions in the production process in real-time. Digital technologies can help enterprises track the entire life cycle of product production, pinpoint the sources of energy waste and carbon emissions, and take targeted measures to reduce the carbon intensity of enterprises. In addition, DTI can promote green offices. For example, green office forms such as paperless work, online office, and hardware reduction through virtualization can reduce carbon emissions from offices, production, and commuting (Abdullah & Lim, 2023). In the supply chain, DTI promotes the control of carbon emissions. DTI can optimize supply chain and logistics management to reduce unnecessary energy consumption and carbon emissions. By establishing a digital supply chain system, companies can visualize and monitor energy and carbon emissions throughout the supply chain, including raw material procurement, product manufacturing, and sales. This will help companies optimize logistics and transportation processes, enhance cooperation with suppliers on carbon reduction, and reduce transportation distances and energy consumption (Yuan & Pan, 2023). This leads to Hypothesis 2:

H2: *DTIs reduce carbon intensity by enabling cleaner production.*

3.3. Improvement of human capital

The DTI relies on digital foundations such as data and algorithms, and enterprises need to have specific digital capabilities, namely "talents, specialized equipment and knowledge for enterprises to carry out digital technology innovation" (Khin & Ho, 2018). When entrepreneurs focus on digital technology and are ready to create new technologies, they will inevitably need to introduce a large number of high-tech talents and equipment, which in turn will improve the level of human capital of the company. Combining digital technology and talent can promote the reorganization of factors and bring innovation opportunities, which has become a meaningful way to achieve net-zero carbon emissions (Yadav et al., 2023). For example, DTI can optimize the factor structure and achieve factor reorganization, promoting technological progress in the energy sector and reducing energy consumption (Du et al., 2023). In the process of DTI, the data element is particularly important, and the proportion of data in enterprises' factor input is increasing. Highly skilled talents can better help enterprises collect and analyze data and provide decision support for enterprise product optimization and process innovation, thereby increasing enterprise output. When enterprises have more talent and data processing capabilities, their willingness and success rate of green innovation in manufacturing are higher (Tian et al., 2022). This not only increases enterprise output but also reduces resource waste and carbon emissions, which in turn reduces carbon intensity. This leads to Hypothesis 3:

H3: *The DTI reduces carbon intensity by increasing human capital.*

4. Research design

4.1. Measurement models

Drawing on Shang et al. (2023) study, this paper constructs a multiple fixed-effects model based on robust standard errors to assess the impact of DTI on carbon emission intensity. The specific model is as follows:

$$\ln cei_{it} = \alpha_0 + \alpha_1 \ln DTI_{it} + \varphi\, control_{it} + FE_{\text{year}} + FE_{\text{indus}} + FE_{\text{firm}} + \varepsilon_{it}. \quad (1)$$

Among them. i is the enterprise, t denotes the year; cei is the carbon emission intensity, DTI is the level of DTI. *control* is the control variables, including R&D investment intensity (R&D), sustainable growth rate (SGR), financing constraints (SA), firm size (SIZE), nature of equity (Stock_NA), profitability of total assets (ROA), asset-liability ratio (ALR), and age of the firm (AGE); FE_{year}, FE_{indus}, and FE_{firm} are year, industry, and firm fixed effects, respectively. To control for possible omitted variable effects; ε_{it} is the random error line; all regressions are clustered to the firm level.

4.2. Variable measurement

4.2.1. Explained variables

Carbon intensity: drawing on Yuan et al. (2023) study, the carbon emissions of listed companies as a proportion of operating income are used to measure the explanatory variable, carbon emission intensity. This paper collects carbon emissions from listed companies' annual disclosed social responsibility reports, sustainability reports, and environmental reports. Suppose the carbon emission data are not disclosed. In that case, their fossil energy consumption and energy consumption data such as electricity and heat consumption are collected, and the carbon emission conversion factor is used to calculate the total carbon emission value of the enterprise (Chen & Zhu, 2022).

4.2.2. Explanatory variables

Digital technological innovation (DTI): There is no unified framework for measuring digital technological innovation. Part of the literature measures it by identifying firms' digital patents (Huang et al., 2023), ignoring the process characteristics of digital technology innovation. The study of Khin and Ho (2018) points out that digital innovation orientation and the underlying capabilities of DTI are important drivers of DTI. Based on this, this paper constructs a measurement index of enterprise DTI including digital innovation attention (diga), digital innovation input (digip), and digital innovation output (digop) from the process and results of DTI. To eliminate the influence of the quantitative scale, we assign 1/3 weight to each of them after standardization and sum them up to get the results of enterprise DTI.

First, entrepreneurs' attention to digital technology is the basis for making DTI (Zahra et al., 2023). Entrepreneurs need to increase their digital focus and understanding of cutting-edge digital technologies to develop a corporate digital strategy and innovation orientation to gain a competitive advantage. Drawing on Zhou et al. (2022), this paper combines natural language processing and textual feature analysis techniques to extract word frequencies related to digital technologies from annual reports of listed firms to measure firms' digital attention (diga).

Secondly, the enterprise's investment of resources in DTI is a guarantee to carry out innovation. Using digital technologies and devices in enterprises can change traditional knowledge and information into digital form and guarantee new DTI (Nambisan et al., 2017; Yoo et al., 2010). For example, AI as a generalized technology can facilitate new technological innovations (Liu et al., 2020). Drawing on previous studies, the ratio of the digital technology-related portion of the year-end intangible asset breakdown to the total intangible assets disclosed in the financial reports of listed companies is used to measure the level of firms' digital infrastructure investment (Zhang et al., 2021). Specifically, when the intangible asset item contains keywords related to digital technology such as "software", "network", "client", "management system", "intelligent platform", etc., the item is defined as "digital technology intangible assets". Then multiple digital technology intangible assets of the same company in the same year are summed up, and their proportion in the intangible assets of the current year is calculated. This is a proxy variable for the extent of digital investment in the company (digip).

Finally, digital patents are an important measure of the outcome of DTI (Corvello et al., 2023). Drawing on the study of Huang et al. (2023), this paper identifies digital technology innovation patents of enterprises based on the IPC information of their patents. Ultimately, digital technology innovation outcomes are measured using digital patent grants (digop).

4.2.3. Control variables

Research and development investment intensity (R&D): R&D investment is key to improving productivity and promoting sustainable growth, and contributes to decoupling economic growth from carbon emissions (Wang & Zhang, 2020). R&D investment is measured using R&D investment as a share of operating income.

Sustainable Growth Rate (SGR): The higher the SGR value, the higher the long-term profitability and competitiveness, which helps to provide stable financial support for the enterprise to reduce carbon emissions, thus reducing the intensity of carbon emissions. Drawing on Kuo and Chang (2021)s study, SGR = return on net assets × (1 − dividend distribution rate).

Financing constraint (SA): Financing constraint is an important factor affecting enterprise performance and willingness to reduce carbon emissions. When the enterprise financing constraint is high, it is difficult for enterprises to carry out green technology innovation and environmental protection investment work, increasing the enterprise pollution emission intensity (Yu et al., 2022). Financing constraint is measured using the SA index.

Enterprise size (SIZE): Generally speaking, the larger the enterprise, the more the managers will pay more attention to their social image and fulfill their environmental responsibilities. Enterprise size is measured using the logarithm of total corporate assets (Oyewo, 2023).

Nature of equity (Stock_NA): For state-owned enterprises (SOEs), the government, as the controlling body, will ask the enterprises to take more social responsibility, and SOEs may invest more money to reduce carbon emissions (Yu & Tsai, 2018). Private enterprises may be better than state-owned enterprises in terms of technological innovation. The nature of the enterprise has an important effect on carbon emission intensity (Yu et al., 2023). It is 1 if the enterprise is state-owned, 2 for private, 3 for foreign, and 4 for other enterprises.

In addition, drawing on previous research (Chen & Zhu, 2022), this paper also chooses total asset profitability (ROA), asset-liability ratio (ALR), and age of the firm (AGE) as control variables.

4.3. Data sources

This paper selects the data of A-share listed companies in Shanghai and Shenzhen from 2009 to 2021 as the research sample (Table 1). This provides up to 12 years of data for the study, a time period that covers the entire process from the initial development of DTI to mature applications. This can help us capture the long-term trends and dynamics of the relationship between DTI and corporate revenue and carbon emissions.

In the field of financial data, WIND and China Stock Market & Accounting Research Database (CSMAR) are the main data sources for research on China issues, covering market data of Chinese listed companies, operational data, and nearly 2,000 indicators. It is one of the most representative, authoritative and complete databases and has been widely used. Therefore, data such as corporate annual reports and financial reports of listed companies in this paper are organized in the WIND database, control variables are mainly collected from CSMAR, and digital patent data comes from the China Research Data Service Platform (CNRDS). ST and period delisting samples were removed, erroneous records were removed, financial companies were deleted, and 27,751 observations were finally obtained. Considering the accuracy of the estimated results, we did not interpolate the missing values, but carried out automatic elimination in the data regression. We exclude the missing data and finally obtain 8,293 valid observations.

From the perspective of the number of enterprises (Figure 2), as the number of listed companies in China increases year by year, the sample enterprises in this paper also show a trend of annual increase. Among them, there were 1,184 sample enterprises in 2009, and 1,718 A-share listed companies in that year, accounting for about 68.92%. In 2021, there will be 3,145 sample enterprises and 4,655 A-share listed companies, accounting for 67.56%. The sample enterprises in each year accounted for about 70% of the total listed companies in that year, which is representative to a certain extent.

Table 1. Descriptive statistics

Variable	Obs	Mean	S.D.	Min	Max.
CEI	27742	4.956	2.716	1.526	18.476
DIGI	8293	0.052	0.068	0	0.543
DIGA	27751	6.366	18.722	0	463
DIGIP	19051	0.003	0.005	0	0.029
DIGOP	10439	14.175	86.203	0	3333
SGR	27744	0.060	0.683	–10.132	98.694
SA	27744	–3.769	0.275	–5.646	–1.740
ROA	27744	0.044	0.182	–3.164	22.005
ALR	27744	0.422	0.222	0.007	10.082
R&D	23717	4.193	3.693	0.022	21.760
Stock_NA	26684	1.680	0.599	1.000	4.000
SIZE	27650	22.167	1.377	15.468	18.636
AGE	27738	17.365	6.009	0.000	63.000

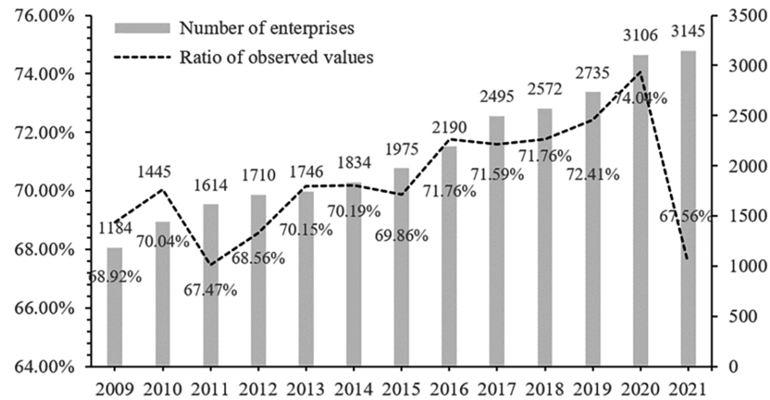

Figure 2. Distribution of sample enterprises over the years

5. Results and discussion

5.1. Benchmark regression

The results of the baseline regression analysis in this paper are shown in Table 2. With no control variables in column (1), and with control variables and year fixed effects in column (2), the regression coefficients of DTI on the carbon emission intensity of enterprises are all significantly negative, implying that enterprises that carry out DTI have lower carbon emission intensity in the average sense. According to the results in column (3), after controlling for enterprise, year and industry fixed effects, the regression coefficient of DTI is –0.0139. The robust standard error of clustering to the enterprise level is significant at the 10% level, which indicates that for every 1% increase in the level of DTI, the carbon intensity of the enterprise will be significantly reduced by 0.0139%. Further, in columns (4)–(6), we regress firms' carbon intensity using digital attention (diga), digital input (digip) and digital innovation output (digop) respectively. The results are all significantly negative, suggesting that the whole DTI proce can positively reduce firms' carbon intensity. The effect of digital attention on carbon intensity is significantly smaller than that of digital input and digital innovation output. This indicates that concrete actions of enterprises are more influential than slogans.

5.2. Robustness tests

To verify the robustness of the estimation results, this paper conducts robustness tests around the dimensions of replacing the explanatory variables, removing the effect of carbon intensity in the previous period, removing the shock of the new crown epidemic, and excluding the effect of typical urban firms.

(1) Substitution of explanatory variables. Differences in the measurement of firms' carbon emissions may also impact onss the estimation results, and this paper draws on the work of (Shang et al., 2023) to use a new estimation method to calculate corporate carbon emissions for robustness testing. Enterprise carbon emissions = (enterprise operating cost / industry main operating cost) × industry carbon emissions. From the results in column (1) of Table 3, it can be seen that after re-measuring enterprises' carbon intensity, DTI can still reduce carbon intensity significantly.

Table 2. Benchmark regression

	(1)	(2)	(3)	(4)	(5)	(6)
	m1	m2	m3	m4	m5	m6
lnDTI	–0.0308***	–0.0142**	–0.0139*			
	(0.0056)	(0.0071)	(0.0071)			
lndiga				–0.0099**		
				(0.0041)		
lndigip					–0.0142***	
					(0.0045)	
lndigop						–0.0128**
						(0.0054)
_cons	1.6034***	5.2594***	5.2905***	5.5484***	4.9996***	5.0044***
	(0.0203)	(0.4201)	(0.4282)	(0.3532)	(0.2974)	(0.3932)
Control Var	NO	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES	YES	YES
Obs	7911	7293	7287	12731	15191	7110
R^2	0.3328	0.3880	0.3921	0.3834	0.3380	0.3789

Note: Robust standard errors clustered to the firm level are in parentheses; * , ** and *** denote significant at the 10%, 5% and 1% levels, respectively. Same for the latter table.

(2) Add the time lag term of enterprise carbon intensity. Considering that the carbon intensity of enterprises may have time series correlation, this paper believes that results in the carbon intensity of enterprises in the current year will be affected by the carbon intensity of previous years. Given this, this paper adds the time lag term of carbon intensity of enterprises in the regression to re-test. The robustness test results are shown in column (2) of Table 3, and the coefficient of DTI is significantly negative, consistent with the benchmark results.

(3) Exclude the impact of the new crown epidemic. We were considering that COVID-19 may bring shocks to business development, such as leading to a reduction in business output, and consequently reducing business energy consumption and carbon emissions. Therefore, we drop the study samples in 2020 and 2021 to exclude the impact of the new crown shock. The results in column (3) of Table 3 show that DTI still significantly reduces carbon emission intensity, consistent with the benchmark regression, after excluding the effects of recession and carbon emission reduction caused by the new crown.

(4) Eliminate firm specific influences. Considering that China's four major municipalities directly under the Central Government and cities such as Hangzhou and Shenzhen have always been at the forefront of DTI. In this paper, firms in these cities are excluded to rule out the effect of regional differences in digital technology development. From the results in column (4), the effect of DTI on carbon emission intensity is –0.0162, which is consistent with the benchmark regression.

(5) In the regression sample, after removing the missing value, the remaining companies are only listed companies with data related to DTI. Companies that did not disclose the data were excluded. As a result, it may be difficult to reveal the actual impact of all corporate DTI on carbon intensity. To test whether such sample selection bias exists, the selection model proposed by Heckman (1979) was adopted in this study. In the first step of the model, Probit model was used to estimate the probability of whether the listed company was observed (Eq. (2)), and Inverse Mill's Ratio (IMR) was calculated. In the second step, IMR is added to Eq. (3) to eliminate sample selectivity bias.

$$Probit\left(\text{DIGI\_dum}_{i,t}\right) = \alpha_0 + \alpha_1 Dyh\_dum_{i,t} + \sum \alpha_k Control_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t}; \quad (2)$$

$$\ln cei_{it} = \alpha_0 + \alpha_1 \ln digi_{it} + \alpha_2 Imr_{i,t} + \sum \alpha_k Control_{i,t} + \sum Ind + \sum Year + \varepsilon_{i,t}. \quad (3)$$

Firstly, in the first stage model, it is defined that if the enterprise makes DTI, then $\text{DIGI\_dum}_{i,t} = 1$, otherwise it is 0. With reference to the study of Ma et al. (2023), whether the firm conducts diversification ("Dyh_dum") is selected as the identification variable of DTI. If the firm operates in only one industry, "Dyh_dum = 0", otherwise it is 1. If enterprises operate across multiple industries, it means that they may face greater uncertainties and operational risks, which will affect whether enterprises choose to implement DTI strategies. But this is not directly related to the amount of DTI.

As can be seen from column (5) of Table 3, Dyh_dum has a negative impact on enterprise DTI. In column (6), after adding IMR to eliminate sample selection bias, the results are still significant at the 5% level. It can be seen that the sample selection problem does not cause obvious bias in the model results, and the estimated results are robust.

Table 3. Robustness test

	(1)	(2)	(3)	(4)	(5)	(6)
	lncei	lncei	lncei	lncei	Digi_dum	lncei
lnDTI	–0.0775***	–0.0136*	–0.0141*	–0.0162**		–0.1435**
	(0.0141)	(0.0073)	(0.0078)	(0.0082)		(0.0070)
Dyh_dum					–0.1089**	
					(0.0550)	
Imr						0.0486
						(0.1342)
_cons	8.2208***	2.1101***	5.4617***	5.8748***	–1.2221	4.9756***
	(0.6856)	(0.3986)	(0.4843)	(0.59312)	(0.7615)	(0.3525)
Control Var	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	NO	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Obs	4748	6407	6186	5083	19902	6872
R^2	0.9636	0.4009	0.4000	0.4008		0.3849

5.3. Endogenous treatment

Consider that endogeneity problems may be caused by missing variables and reverse causation. This paper uses more dimensional fixed effects, instrumental variables method, and double difference method to alleviate the possible endogeneity problem.

(1) Multidimensional fixed effects. Although we have tried our best to control the variables related to carbon emission intensity, it is still inevitable that some variables will be omitted. Therefore, this paper further adds city fixed effects and city-year interaction effects to the baseline regression to alleviate the problem of possible omitted variables. From the results in columns (1)–(2) of Table 4, it can be seen that after controlling for city and interaction effects, DTI still significantly reduces corporate carbon intensity.

(2) Instrumental variables approach. To mitigate the endogeneity problem caused by two-way causality. In this paper, the mean value of DTI (DTI_m) in the same city and industry but excluding the firm itself and the volume of postal and telecommunications business (HPT) in the city where the firm is located in 1984 are selected as instrumental variables for the firm's DTI. On the one hand, firms' DTI decisions are usually influenced by the level of the mean DTI of other firms in the same city-same industry. Still, the mean DTI of other firms does not directly affect the carbon intensity of this firm (Chen et al., 2022). On the other hand, the application and innovation of digital technology depend on improving postal and telecommunication communication infrastructure, and the postal and telecommunication communication infrastructure in the region where the enterprise is located may affect the level of DTI. However, the historical postal and telecommunication does not affect the carbon intensity of the current enterprise, which meets the condition of exogeneity. In this paper, postal and telecommunication business per capita in 1984 in the region where the firm is located is selected to portray the level of postal and telecommunication communication. Specifically, this paper utilizes these two variables to construct a new instrumental variable IV = DTI_m * HPT, which is regressed using the 2SLS method. From the results in column (3) of Table 4, IV significantly contributes to DTI as expected. Column (4), the second stage regression results show that DTI significantly reduces firms' carbon intensity. The LM and Wald F statistics indicate that the instrumental variables are reasonable.

(3) Introducing exogenous policy shocks: In 2014, China's Ministry of Industry and Information Technology (MIIT) launched a nationwide pilot program to integrate informationization and industrialization, focusing on strategic transformation, process optimization, technological innovation, and data development and utilization. Enterprises that meet the criteria are recognized as pilot enterprises, meaning they are at the forefront of DTI and have a certain degree of exemplary and leading role. The "informationization-industrialization" integration pilot program is important in promoting DTI. Pilot data come from the pilot list published by the General Office of the MIIT. Based on the above, this paper sets the policy shock variable DID: DID takes the value of 1 when the enterprise belongs to the pilot and the time is in the year of pilot establishment or later, otherwise it takes the value of 0. The coefficient of DID in Column (5) of Table 4 is –0.0342, meaning that after implementing the pilot integration of informationization and industrialization, the carbon emission intensity of local enterprises is significantly reduced.

Table 4. Endogenous treatments

Model	More stringent FE		2SLS		DID
Variable	lncei	lncei	lnDTI	lncei	lncei
	(1)	(2)	(3)	(4)	(5)
lnDTI	–0.0139*	–0.0140**		–0.0697*	
	(0.0129)	(0.0072)		(0.0372)	
IV			0.0081***		
			(0.0011)		
DID					–0.0342***
					(0.0094)
_cons	5.2445***	5.2624***	–3.9884***	2.1470***	3.0667***
	(0.4283)	(0.4271)	(0.3996)	(0.2094)	(0.1125)
Control Var	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
City FE	YES	YES	NO	NO	NO
City#Year	NO	YES	NO	NO	NO
Kleibergen-Paap LM statistic				48.582*** (0.0002)	
Cragg-Donald Wald F statistic				57.716 [16.38]	
Obs	7276	7276	5496	5496	22383
R^2	0.3950	0.3962	0.2446	0.0843	0.3043

5.4. Mechanism testing

The theoretical hypotheses section identifies operational efficiency, cleaner production, and human capital enhancement as the three channels through which DTIs affect the carbon intensity. Referring to Pu and Fei (2022), this paper constructs the following model for testing:

$$\ln cei_{it} = \alpha_0 + \alpha_1 \ln DTI_{it} + \varphi control_{it} + FE_{year} + FE_{indus} + FE_{firm} + FE_{city} + \varepsilon_{it}; \tag{4}$$

$$M_{it} = \alpha_0 + \alpha_1 \ln DTI_{it} + \varphi Control_{it} + FE_{year} + FE_{indus} + FE_{firm} + FE_{city} + \varepsilon_{it}; \tag{5}$$

$$\ln cei_{it} = \alpha_0 + \alpha_1 \ln DTI_{it} + \alpha_2 M_{it} + \varphi Control_{it} + FE_{year} + FE_{indus} + FE_{firm} + FE_{city} + \varepsilon_{it}. \tag{6}$$

where M_{it} denotes the mechanism variable tested, which contains business operational efficiency, cleaner production, and enhancement of human capital. The other variables are defined by Eq. (1).

5.4.1. Mechanistic tests of operational efficiency

The process of DTI can optimize the production process and management structure of enterprises. Through customized and flexible production, it can effectively improve the operational efficiency of inventory and capital. Based on this, we use the working capital turnover ratio measure. the larger the FOE indices, the higher the enterprise's operational efficiency. The coefficient of DTI in column (1) of Table 5 is significant, indicating the existence of mediation effect. Column (2) tests the effect of DTI on firms' operational efficiency, and the estimated coefficient of DTI is significantly positive at the 1% level, indicating that DTI can effectively improve the operational efficiency of firms' inventories. Furthermore, the mediating variable is added to regression model (2), and from the test results in column (3), the effect of operational efficiency on carbon intensity is –0.0191, which passes the 5% significance test. This indicates that DTI can improve the operational efficiency of enterprises and bring more output for unit input factors, reducing carbon intensity. This proves hypothesis H1.

Table 5. Mechanism test: operational efficiency

Variable	Carbon emission intensity	Operational efficiency	Carbon emission intensity
	lncei	lnfoe	lncei
	(1)	(2)	(3)
lnDTI	–0.0139*	0.0528**	–0.0121
	(0.0129)	(0.0215)	(0.0097)
lnfoe			–0.019^{1*}*
			(0.0072)
_cons	5.2445***	1.9084	5.8380***
	(0.4283)	(1.5369)	(1.0344)
Control Var	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
City FE	YES	YES	YES
Obs	7276	5635	5635
R^2	0.3950	0.8714	0.5053

5.4.2. Mechanism test for cleaner production

The mechanism analysis shows that DTI realizes clean production through energy saving and green office, reducing carbon emission intensity. This paper uses the following three indicators to reflect a company's clean production capacity (CP) for mechanism testing. The data comes from the enterprise ESG database of the China Research Data Service Platform (CNRDS), which makes judgments based on the content disclosed by listed companies in ESG reports. (1) Energy conservation. Companies disclose policy measures or technologies to save energy in ESG reports. Including the proportion of renewable energy use, energy-saving target, energy-saving system, energy-saving measures, etc., if yes, is 1, no is 0. (2) Green office. Whether the company has a green office policy or practice. For example, telecommuting, paperless office, water and electricity saving, paper saving, and reducing carbon emissions from employee transportation. If yes, it is 1, if no, it is 0. (3) Whether environmentally beneficial products are developed. It mainly refers to products that have a low environmental impact during the product life cycle. For example, in the product design, production, use or disposal process can reduce waste, reduce carbon emissions, save energy and so on.If there is 1, not 0.

The three are then added together, and the larger the value is, the higher the level of cleaner production carried out by the company will be. From the results in column (2) of Table 6, DTI significantly increases the cleaner production capacity of enterprises. From the column test (3) results, the estimated coefficient of DTI is –0.0136 and the effect of cleaner production on carbon intensity is –0.0352. This indicates that digital technologies such as smart production, IoT and energy monitoring can improve the ecological impact of manufacturing processes and reduce carbon intensity. The research of Amjad et al. (2021) concludes that digital technologies can help to reduce energy use, and promote cleaner production. As a result, it will reduce emissions from the manufacturing sector by 54.16%. Hypothesis H2 is proved.

Table 6. Mechanism test: cleaner production

Variable	Carbon emission intensity	Cleaner production	Carbon emission intensity
	lncei	lncp	lncei
	(1)	(2)	(3)
lnDTI	–0.0139*	0.0090*	–0.0136*
	(0.0129)	(0.0053)	(0.0071)
lncp			–0.0352**
			(0.0160)
_cons	5.2445***	–0.1751	5.2385***
	(0.4283)	(0.3164)	(0.4266)
Control Var	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
City FE	YES	YES	YES
Obs	7276	7276	7276
R^2	0.3950	0.7733	0.3955

5.4.3. Mechanisms to enhance human capital tested

The impact of DTI on enterprise factor inputs is mainly manifested in the two aspects of data factor and talent factor, especially on the labor force structure (C. Yang, 2022). Considering data availability, the improvement of human capital (IHC) is measured using the percentage of employees with graduate and higher degrees in the firm. The results in column (2) of Table 7 show that DTI significantly increases the percentage of highly educated employees, as shown by the fact that for every 1% increase in the level of digital technology innovation, the percentage of highly educated employees will increase by 0.0685%. This is in line with C. Yang (2022) findings, which suggest that the development and application of AI significantly reduces the low-skilled labor force of enterprises and increases the proportion of high-skilled labor force (with postgraduate education). The results in column (3) show that the increase in human capital significantly reduces the carbon intensity of firms. The research of Bano et al. (2018) also corroborates this view that an increase in human capital can reduce carbon emissions without reducing output. Thus, hypothesis H3 is verified.

Table 7. Mechanism test: enhancing human capital

Variable	Carbon emission intensity	Improve human capital	Carbon emission intensity
	lncei	ihc	lncei
	(1)	(2)	(3)
lnDTI	–0.0266**	0.0685***	–0.0012
	(0.0129)	(0.0222)	(0.0126)
ihc			–0.0194*
			(0.0115)
_cons	5.1986***	1.0838	5.0152***
	(0.4283)	(1.0466)	(0.5887)
Control Var	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
City FE	YES	YES	YES
Obs	7288	5064	5064
R^2	0.3955	0.9384	0.3982

5.5. Heterogeneity analysis

5.5.1. Impact of the external environment

(1) Government Digital Attention

As governments pay increasing attention to DTI, policies change, impacting firms' behavior. As a result, this paper examines whether the government's digital attention affects the impact of DTI on carbon intensity. The government work report reveals the government's work priorities and is important in guiding corporate strategies. Drawing on Zhou et al. (2022), this paper collects government work reports from various cities in China. It selects more than 120 words related to digital technology to calculate the government's digital focus and categorize them into high, moderate and low focus. From the results in columns (1)–(3) of Table 8, the impact of DTI on carbon intensity is differentiated by local governments' attention to DTI. Only when the government's attention to DTI is maintained at an appropriate level, enterprises' DTI can significantly reduce carbon intensity, whose coefficient is –0.0348. Too much attention and not enough attention will not make DTI work as well as it should. This may be because when the government focuses too much on digital innovation, companies will blindly increase their digital innovation and digital transformation efforts to meet government policies. This will reduce the efficiency of investment increase costs, and put enterprises under greater production and financial pressure (He & Chen, 2023). As a result, it is difficult for enterprises to steadily promote enterprise production and emission reduction.

(2) Level of intellectual property protection

Intellectual property protection is an important method to safeguard the patent rights and interests of enterprises, which is conducive to maintaining the innovation power of enterprises and promoting the transformation and application of patent achievements. Accordingly, the impact of the level of intellectual product protection in the city where the enterprise is located is further examined. In this paper, the number of intellectual property trial settlements in the city where the enterprise is located is used as a proxy indicator for the intensity of intellectual property judicial protection, and it is categorized into high intellectual property protection and low intellectual property protection based on the annual average value. The data comes from the legal information database of Beida Faber. According to the results in columns (4)–(5) of Table 8, only when the level of intellectual property protection in the city is high, the impact of DTI on carbon intensity is more significant, with a coefficient of –0.0189. Intellectual property protection is the key to maintaining the benefits of enterprise digital technology innovation (Teece, 2018). Suppose local governments do not pay attention to intellectual property protection. In that case, it is difficult to defend the rights of DTI when they are free-riding, which will seriously weaken the innovation drive of enterprises. Thus, it isn't easy to exert the impact of DTI on the carbon intensity of enterprises.

Table 8. Impact of the external environment

	Government digital attention			Intellectual property protection	
	High attention	Moderate attention	Low attention	High protection	Low protection
	(1)	(2)	(3)	(4)	(5)
lnDTI	–0.0183	–0.0348***	0.0167	–0.0189*	–0.0113
	(0.0204)	(0.0108)	(0.0195)	(0.0114)	(0.0105)
_cons	4.7952***	5.3233***	5.2833***	5.2226***	5.9325***
	(1.1036)	(0.6185)	(1.3080)	(0.5646)	(0.7786)
Control Var	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Obs	1263	3412	1322	3586	3056
R^2	0.5382	0.4600	0.4910	0.4090	0.4254

5.5.2. Impact of internal conditions

(1) Business life cycle

According to the business life cycle theory, firms in different life cycles differ regarding operational capabilities, R&D investment and innovation (Wen et al., 2022) . Therefore, the impact of DTI on carbon emission intensity may show differences depending on their life cycle. Following (Wen et al., 2022), we classify firms into three stages: growth, maturity, and decline. From the results in columns (1)–(3) of Table 9, only when the firms belong to the maturity stage, the DTI can significantly reduce the carbon intensity, with a coefficient of –0.0352. In contrast, when the firms belong to the growth stage and the decline stage, the DTI fails to produce a reduction in carbon intensity. The possible reason is that mature enterprises have more capital accumulation and are more willing to drive high-quality development through innovation than enterprises in the growth and decline periods (Luo et al., 2023). The reasons why Growing firms tend to be "utilitarian" in the allocation of funds, and DTI and carbon emission reduction projects do not realize intuitive financial returns in a short period are usually not prioritized. Enterprises in the declining stage have rigid systems, ineffective management, and redundant structures that make it difficult for them to carry out DTI activities, and they lack the willingness to make efforts to reduce carbon emissions in their enterprises.

(2) High-tech enterprise qualification

Considering the qualifications of enterprises may lead to differences in the impact effects of DTI. According to the classification standard of China's High-tech Industry Classification 2017[2], this paper divides enterprises into high-tech enterprises and non-high-tech enterprises for testing. The results in columns (4) and (5) of Table 9 show that the effect of DTI in reducing the carbon emission intensity of enterprises is more significant in high-tech enterprises. There is no significant effect for low-tech firms. This may be because non-high-tech enterprises usually lack advantages in human capital and technology accumulation, which is not conducive to DTI, and it isn't easy to exert the carbon emission reduction effect of DTI.

Table 9. Effects of internal conditions I

	Enterprise life cycle			High-tech enterprise qualification	
	Growth type	Mature type	Recession type	High-tech industry	Low-technology industry
	(1)	(2)	(3)	(4)	(5)
lnDTI	–0.0108	–0.0352**	–0.0022	–0.0198*	–0.0084
	(0.0151)	(0.0152)	(0.0131)	(0.0117)	(0.0095)
_cons	1.8026**	2.9936***	2.1217***	5.7340***	5.0898***
	(0.7668)	(0.9362)	(0.6989)	(0.6113)	(0.6519)
Control Var	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Obs	1452	1726	2398	3426	3833
R^2	0.4831	0.4584	0.5024	0.4023	0.4061

(3) Factor Intensity

Firms with different levels of production factor intensity have significantly different preferences for DTI. To explore this difference in factor intensity, we classify our sample firms into labor-intensive, capital-intensive and technology-intensive. With reference to the method Lu and Dang (2014), firstly, the proportion of fixed assets in total assets and the proportion of R&D expenditure in employee compensation of each industry are calculated respectively.

[2] The high-tech industry specified in this classification refers to the industry with relatively high R&D investment intensity in the national economy. It mainly includes six categories: pharmaceutical manufacturing, aviation, spacecraft and equipment manufacturing, electronic and communication equipment manufacturing, computer and office equipment manufacturing, medical equipment and instrumentation manufacturing, information chemical manufacturing.

Then, all industries are divided into three categories: labor intensive, capital intensive and technology intensive by using the deviation leveling method in cluster analysis. The results in Table 10 show that DTI has a good carbon intensity reduction effect in technology-intensive firms. It has no significant effect on carbon intensity in labor-intensive and capital-intensive firms. This finding is consistent with Liu et al. (2022a) which argues that AI can reduce the carbon intensity of technology-intensive industries. Unlike Liu et al. (2022a), who argue that this effect also exists in labor-intensive industries, it does not exist in labor-intensive firms for DTI. We argue that DTI differs from the simple application of artificial intelligence technology. The process of DTI from corporate strategy, innovation investment is very long, and the risk of uncertainty is large. For labor-intensive firms, the lack of such innovation willingness and ability makes it difficult to play the role of DTI. In technology-intensive enterprises, entrepreneurs focus on cutting-edge DTI for a long time, have more high-tech talents and capital, and have a higher probability of successful DTI. DTI can promote total factor productivity and bring more economic output to enterprises, while digital technology has certain green attributes and thus performs more significantly.

Table 10. Impact of internal conditions II

	labor-intensive	Capital intensive	technology-intensive
	(1)	(2)	(3)
lnDTI	–0.0078	0.0259	–0.0269***
	(0.0152)	(0.0174)	(0.0096)
_cons	4.1042***	2.8499	6.1738***
	(1.0890)	(1.8556)	(0.4942)
Control Var	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Obs	1290	817	5127
R^2	0.4598	0.4080	0.3859

5.5.3. Impact pathway differences

Benchmark regressions show that the entire process of DTI (from digital attention, digital inputs to digital patent outputs) significantly reduces the carbon emission intensity of enterprises. The reduction of carbon emission intensity may come from several aspects. Firstly, carbon emission is reduced and enterprise output is unchanged or increased. Secondly, output is increased but carbon emission is unchanged or reduced. Thirdly, the magnitude of output increase is greater than the magnitude of carbon emission increase. So how exactly does the DTI process affect carbon intensity? Can the effect of increasing output without increasing carbon be realized? To this end, we use digital attention, digital inputs, and digital patent outputs to regress on corporate carbon emissions and operating income, respectively. In terms of digital attention (columns 1 and 4 of Table 11), business managers' increased digital attention does not reduce carbon emissions, but can significantly increase business revenue. In terms of digital inputs (columns 2 and 5 of Table 11), the coefficient of the impact of the use of digital technology and equipment on carbon emissions is 0.0038, which is not significant, and the coefficient of the impact on business revenues is 0.0197, which passes the 1% significance test. This suggests that digital attention and digital technology inputs do not significantly affect carbon emissions, but have a significant incremental effect on business output, reducing carbon intensity. In termRegardingl patent output (columns 3 and 6 of Table 11), digital technology patents can significantly reduce total carbon emissions but fail to increase firm output in the short run. This may be due to the high upfront investment in new digital technology innovation, the use of this new technology itself has high technological attributes and green bias, and the impact of the invention of new digital technology on carbon emissions can have a quick effect. However, in the short term, it may be difficult to cover the cost of innovation and contribute significantly to revenue.

Table 11. Impact pathway differences: short-term impacts

	Impact on total carbon emissions			Impact on corporate revenue		
	$lnco_2$	$lnco_2$	$lnco_2$	lnincom	lnincom	lnincom
	(1)	(2)	(3)	(4)	(5)	(6)
lndiga	0.0059			0.0161***		
	(0.0062)			(0.0036)		
lndigip		0.0038			0.0197***	
		(0.0072)			(0.0049)	
lndigop			–0.0144*			0.0027
			(0.0083)			(0.0048)
_cons	4.5030***	4.2328***	4.3430***	–0.8113***	–0.8625***	–0.5183
	(0.5540)	(0.4727)	(0.6313)	(0.3119)	(0.2942)	(0.3662)
Control Var	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Obs	12711	15153	7095	12731	15191	7110
R^2	0.9359	0.9199	0.9360	0.9817	0.9747	0.9825

To examine whether there is a long-term non-linear relationship, we add each variable's quadratic terms to the model. Regarding the effect of total carbon emissions, model (1) in Table 12 shows that digital attention does not significantly affect carbon emissions in the short or long term. Model (2) shows that using digital techniques and equipment raises total corporate carbon emissions. Model (3) shows that digital technology innovation still raises total corporate carbon emissions for the long term. This suggests a certain rebound effect of DTI, where new technologies can only reduce carbon emissions in the short time, and then raise carbon emissions once these new digital technologies are used in large quantities. Regarding the impact of enterprise income, the results of models (4)–(6) all indicate that digital attention, digital inputs and patents can increase enterprise income in the long run.

Table 12. Impact pathway differences: long-term impacts

	Impact on total carbon emissions			Impact on corporate revenue		
	$lnco_2$	$lnco_2$	$lnco_2$	lnincom	lnincom	lnincom
	(1)	(2)	(3)	(4)	(5)	(6)
lndiga	0.0254			0.0625^{***}		
	(0.0290)			(0.0170)		
$lndiga^2$	0.0022			0.0051^{***}		
	(0.0031)			(0.0018)		
lndigip		0.0485^{***}			0.0855^{***}	
		(0.0156)			(0.0101)	
$lndigp^2$		0.0053^{***}			0.0078^{***}	
		(0.0016)			(0.0010)	
lndigop			0.0753			0.0585^{**}
			(0.0474)			(0.0291)
$lndigop^2$			0.0070^{*}			0.0043^{**}
			(0.0036)			(0.0022)
_cons	4.5723^{***}	4.3252^{***}	4.5590^{***}	-0.6464^{**}	-0.7259^{**}	-0.3837
	(0.5735)	(0.4751)	(0.6392)	(0.3233)	(0.2943)	(0.3728)
Control Var	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Obs	12711	15153	7095	12731	15191	7110
R^2	0.9359	0.9199	0.9360	0.9817	0.9747	0.9825

In the period from 2009 to 2021, China's economic development and industrial structure development have changed significantly. DTI has promoted the rapid development of high-tech industries, as well as the digital transformation of traditional manufacturing industries, which has improved production efficiency. A large number of studies have proved this point, but these studies lack assessment of the negative environmental effects that may be caused by large-scale digital technology application (Zhang et al., 2023). DTI has led to new sources of energy consumption growth. In particular, data centers and cloud computing require a lot of energy consumption and may not reduce carbon emissions (Jones, 2018). This point has not received enough attention. The same is true of regulation. During this period, the Chinese government significantly strengthened the implementation of environmental regulations and put forward clear requirements for carbon emission reduction (Pan et al., 2019). However, these policies are more aimed at traditional industries than the digital economy. This can result in data center energy consumption and electronic equipment production processes that are not adequately regulated. In addition, in recent years, the large-scale use of digital technology has caused a degree of carbon rebound, and DTI has not reduced the total carbon emissions.

6. Conclusions

Clarifying the impact of DTI on the carbon emission intensity of enterprises is of great significance for achieving stable economic growth and the goal of "double carbon". Based on enterprise micro-data, this paper systematically measures enterprise DTI level from the perspective of the process of DTI (digital attention, input and output). From the aspects of operational efficiency, cleaner production and human capital improvement, this paper reveals the influence mechanism of DTI on carbon emission intensity of enterprises.

Our study confirms that digitization, as measured by digital word frequency, does not affect actual production and has no effect on carbon reduction. We fill this research gap. Although DTI can significantly reduce carbon intensity, the reduction in carbon intensity is more because DTI brings more economic output, rather than directly reducing carbon emissions. In the long run, digital investment and digital patents also have a carbon rebound effect. In addition, the external environment and internal conditions such as government digital attention, intellectual property protection, enterprise life cycle, industry attributes, and factor intensity will make the impact of DTI on carbon intensity significantly heterogeneous.

The theoretical value of this study is that it answers the question of how DTI affects the carbon emission intensity of enterprises, and empirically tests its impact. Our research shows that the frequency of digital words in corporate annual reports does not affect the actual carbon intensity, but plays more of a baton role. More practically, this study helps to remind business managers and policy makers that the DTI is not a panacea for reducing carbon emissions, but may also bring carbon rebound effects. Therefore, it is necessary to strengthen the collaborative innovation of digital technology and green technology in the future, and encourage enterprises to carry out greener DTI. Government departments also need to speed up legislation related to DTI and improve the level of intellectual property protection.

This paper examines the impact of corporate DTI on carbon intensity, it draws some interesting conclusions. However, considering the availability of data, this paper only uses the data of listed companies in China, and the conclusion can only represent relatively high-quality listed companies. Admittedly, there are many unlisted companies of all kinds in China, and therefore cannot be generalized to the broader context of China's financial markets. In the future, the study sample can be expanded to conduct more extensive studies. In addition, the impact of some cutting-edge digital technologies deserves attention, such as edge computing, quantum computing, and so on. These new digital technologies could enable scientists to better understand the dynamics of climate change, predict its impacts, and develop mitigation and adaptation strategies.

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Competing interests

Authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Abdullah, N., & Lim, A. (2023). The incorporating sustainable and green IT practices in modern IT service operations for an environmentally conscious future. *Journal of Sustainable Technologies and Infrastructure Planning*, *7*(3), 17–47. https://publications.dlpress.org/index.php/JSTIP/article/view/33

Accenture. (2022). *Digital transformation*: *A sustainable evolutionary journey*. www.accenture.cn/cn-zh/insights/strategy/china-digital-transformation-index-2022

Amjad, M. S., Rafique, M. Z., & Khan, M. A. (2021). Leveraging optimized and cleaner production through Industry 4.0. *Sustainable Production and Consumption*, *26*, 859–871. https://doi.org/10.1016/j.spc.2021.01.001

Awan, U., Gölgeci, I., Makhmadshoev, D., & Mishra, N. (2022). Industry 4.0 and circular economy in an era of global value chains: What have we learned and what is still to be explored? *Journal of Cleaner Production*, *371*, Article 133621. https://doi.org/10.1016/j.jclepro.2022.133621

Bano, S., Zhao, Y., Ahmad, A., Wang, S., & Liu, Y. (2018). Identifying the impacts of human capital on carbon emissions in Pakistan. *Journal of Cleaner Production*, *183*, 1082–1092. https://doi.org/10.1016/j.jclepro.2018.02.008

Bianchini, S., Damioli, G., & Ghisetti, C. (2023). The environmental effects of the "twin" green and digital transition in European regions. *Environmental and Resource Economics*, *84*(4), 877–918. https://doi.org/10.1007/s10640-022-00741-7

BP. (2022). *Statistical review of world energy*. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

Chan, C. M., Teoh, S. Y., Yeow, A., & Pan, G. (2019). Agility in responding to disruptive digital innovation: Case study of an SME. *Information Systems Journal*, *29*(2), 436–455. https://doi.org/10.1111/isj.12215

Chang, Y. F., Chen, C. S., & Zhou, H. (2009). Smart phone for mobile commerce. *Computer Standards & Interfaces*, *31*(4), 740–747. https://doi.org/10.1016/j.csi.2008.09.016

Chen, W., Zhang, L., Jiang, P., Meng, F., & Sun, Q. (2022). Can digital transformation improve the information environment of the capital market? Evidence from the analysts' prediction behaviour. *Accounting & Finance*, *62*(2), 2543–2578. https://doi.org/10.1111/acfi.12873

Chen, Y., & Zhu, Z. (2022). Liability structure and carbon emissions abatement: Evidence from Chinese manufacturing enterprises. *Environmental and Resource Economics*, *83*(2), 481–507. https://doi.org/10.1007/s10640-022-00649-2

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, *50*(7), Article 104289. https://doi.org/10.1016/j.respol.2021.104289

Ciriello, R. F., Richter, A., & Schwabe, G. (2018). Digital innovation. *Business & Information Systems Engineering*, *60*, 563–569. https://doi.org/10.1007/s12599-018-0559-8

Cong, L. W., Xie, D., & Zhang, L. (2021). Knowledge accumulation, privacy, and growth in a data economy. *Management Science*, *67*(10), 6480–6492. https://doi.org/10.1287/mnsc.2021.3986

Corvello, V., Belas, J., Giglio, C., Iazzolino, G., & Troise, C. (2023). The impact of business owners' individual characteristics on patenting in the context of digital innovation. *Journal of Business Research*, *155*, Article 113397. https://doi.org/10.1016/j.jbusres.2022.113397

Du, J., Shen, Z., Song, M., & Zhang, L. (2023). Nexus between digital transformation and energy technology innovation: An empirical test of A-share listed enterprises. *Energy Economics*, *120*, Article 106572. https://doi.org/10.1016/j.eneco.2023.106572

Fernando, Y., & Hor, W. L. (2017). Impacts of energy management practices on energy efficiency and carbon emissions reduction: a survey of Malaysian manufacturing firms. *Resources, Conservation and Recycling*, *126*, 62–73. https://doi.org/10.1016/j.resconrec.2017.07.023

Ghenai, C., Husein, L. A., Al Nahlawi, M., Hamid, A. K., & Bettayeb, M. (2022). Recent trends of digital twin technologies in the energy sector: A comprehensive review. *Sustainable Energy Technologies and Assessments*, *54*, Article 102837. https://doi.org/10.1016/j.seta.2022.102837

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Gu, J. (2022). Sharing economy, technological innovation and carbon emissions: Evidence from Chinese cities. *Journal of Innovation* & *Knowledge*, *7*(3), Article 100228. https://doi.org/10.1016/j.jik.2022.100228

He, L., & Chen, K. (2023). Digital transformation and carbon performance: Evidence from firm-level data. *Environment*, *Development and Sustainability*. https://doi.org/10.1007/s10668-023-03143-x

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*: *Journal of the Econometric Society*, *47*(1), 153–161. https://doi.org/10.2307/1912352

Hilb, M. (2020). Toward artificial governance? The role of artificial intelligence in shaping the future of corporate governance. *Journal of Management and Governance*, *24*, 851–870. https://doi.org/10.1007/s10997-020-09519-9

Huang, Q., Xu, C., Xue, X., & Zhu, H. (2023). Can digital innovation improve firm performance: Evidence from digital patents of Chinese listed firms. *International Review of Financial Analysis*, *89*, Article 102810. https://doi.org/10.1016/j.irfa.2023.102810

Hund, A., Wagner, H., Beimborn, D., & Weitzel, T. (2021). Digital innovation: Review and novel perspective. *The Journal of Strategic Information Systems*, *30*(4), Article 101695. https://doi.org/10.1016/j.jsis.2021.101695

IEA. (2021). *Global Energy Review 2021*. https://www.iea.org/reports/global-energy-review-2021/co2-emissions

Jones, N. (2018). How to stop data centres from gobbling up the world's electricity. *Nature*, *561*(7722), 163–167. https://doi.org/10.1038/d41586-018-06610-y

Khin, S., & Ho, T. C. (2018). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, *11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083

Kuo, L., & Chang, B. (2021). The affecting factors of circular economy information and its impact on corporate economic sustainability-Evidence from China. *Sustainable Production and Consumption*, *27*, 986–997. https://doi.org/10.1016/j.spc.2021.02.014

Lee, Y., & Yang, C. (2014). The relationships among network ties, organizational agility, and organizational performance: A study of the flat glass industry in Taiwan. *Journal of Management* & *Organization*, *20*(2), 206–226. https://doi.org/10.1017/jmo.2014.32

Li, J., Ma, S., Qu, Y., & Wang, J. (2023). The impact of artificial intelligence on firms' energy and resource efficiency: Empirical evidence from China. *Resources Policy*, *82*, Article 103507. https://doi.org/10.1016/j.resourpol.2023.103507

Liu, J., Chang, H., Forrest, J. Y., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors. *Technological Forecasting and Social Change*, *158*, Article 120142. https://doi.org/10.1016/j.techfore.2020.120142

Liu, J., Liu, L., Qian, Y., & Song, S. (2022a). The effect of artificial intelligence on carbon intensity: Evidence from China's industrial sector. *Socio-Economic Planning Sciences*, *83*, Article 101002. https://doi.org/10.1016/j.seps.2020.101002

Liu, J., Yu, Q., Chen, Y., & Liu, J. (2022b). The impact of digital technology development on carbon emissions: A spatial effect analysis for China. *Resources*, *Conservation and Recycling*, *185*, Article 106445. https://doi.org/10.1016/j.resconrec.2022.106445

Liu, Y., Dong, J., Mei, L., & Shen, R. (2023). Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation*, *119*, Article 102458. https://doi.org/10.1016/j.technovation.2022.102458

Lu, J., & Li, H. (2024). Can digital technology innovation promote total factor energy efficiency? Firm-level evidence from China. *Energy*, *293*, Article 130682. https://doi.org/10.1016/j.energy.2024.130682

Lu, T., & Dang, Y. (2014). Corporate governance and innovation: Differences among industry categories. *Economic Research Journal*, *49*(06), 115–128 (in Chinese).

Luo, G., Guo, J., Yang, F., & Wang, C. (2023). Environmental regulation, green innovation and high-quality development of enterprise: Evidence from China. *Journal of Cleaner Production*, *418*, Article 138112. https://doi.org/10.1016/j.jclepro.2023.138112

Ma, D., & Zhu, Q. (2022). Innovation in emerging economies: Research on the digital economy driving high-quality green development. *Journal of Business Research*, *145*, 801–813. https://doi.org/10.1016/j.jbusres.2022.03.041

Ma, W., Duan, X., & Tang, Y. (2023). Enterprise sustainable development and green fund concern: The analysis and test of R&D from listed companies in China. *Energy Economics*, *121*, Article 106654. https://doi.org/10.1016/j.eneco.2023.106654

Mäkitie, T., Hanson, J., Damman, S., & Wardeberg, M. (2023). Digital innovation's contribution to sustainability transitions. *Technology in Society*, *73*, Article 102255. https://doi.org/10.1016/j.techsoc.2023.102255

Markus, M. L., & Nan, W. V. (2020). Theorizing the connections between digital innovations and societal transformation: Learning from the case of M-Pesa in Kenya. In *Handbook of digital innovation* (pp. 64–82). Edward Elgar Publishing. https://doi.org/10.4337/9781788119986.00013

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management. *Mis Quarterly*, *41*(1), 223–238. https://doi.org/10.25300/MISQ/2017/41:1.03

Oyewo, B. (2023). Corporate governance and carbon emissions performance: International evidence on curvilinear relationships. *Journal of Environmental Management*, *334*, Article 117474. https://doi.org/10.1016/j.jenvman.2023.117474

Pan, X., Pan, X., Li, C., Song, J., & Zhang, J. (2019). Effects of China's environmental policy on carbon emission efficiency. *International Journal of Climate Change Strategies and Management*, *11*(3), 326–340. https://doi.org/10.1108/IJCCSM-12-2017-0206

Peng, Y., & Tao, C. (2022). Can digital transformation promote enterprise performance? – From the perspective of public policy and innovation. *Journal of Innovation* & *Knowledge*, *7*(3), Article 100198. https://doi.org/10.1016/j.jik.2022.100198

Pu, Z., & Fei, J. (2022). The impact of digital finance on residential carbon emissions: Evidence from China. *Structural Change and Economic Dynamics*, *63*, 515–527. https://doi.org/10.1016/j.strueco.2022.07.006

Ranta, V., Aarikka-Stenroos, L., & Väisänen, J. (2021). Digital technologies catalyzing business model innovation for circular economy – Multiple case study. *Resources*, *Conservation and Recycling*, *164*, Article 105155. https://doi.org/10.1016/j.resconrec.2020.105155

Sadorsky, P. (2012). Information communication technology and electricity consumption in emerging economies. *Energy Policy*, *48*, 130–136. https://doi.org/10.1016/j.enpol.2012.04.064

Saia, A. (2023). Digitalization and CO2 emissions: Dynamics under R&D and technology innovation regimes. *Technology in Society*, *74*, Article 102323. https://doi.org/10.1016/j.techsoc.2023.102323

Shang, Y., Raza, S. A., Huo, Z., Shahzad, U., & Zhao, X. (2023). Does enterprise digital transformation contribute to the carbon emission reduction? Micro-level evidence from China. *International Review of Economics* & *Finance*, *86*, 1–13. https://doi.org/10.1016/j.iref.2023.02.019

Shen, Y., Yang, Z., & Zhang, X. (2023). Impact of digital technology on carbon emissions: Evidence from Chinese cities. *Frontiers in Ecology and Evolution*, *11*, Article 1166376. https://doi.org/10.3389/fevo.2023.1166376

Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, *47*(8), 1367–1387. https://doi.org/10.1016/j.respol.2017.01.015

Tian, H., Li, Y., & Zhang, Y. (2022). Digital and intelligent empowerment: Can big data capability drive green process innovation of manufacturing enterprises? *Journal of Cleaner Production*, *377*, Article 134261. https://doi.org/10.1016/j.jclepro.2022.134261

Un, C. A., & Asakawa, K. (2015). Types of R&D collaborations and process innovation: The benefit of collaborating upstream in the knowledge chain. *Journal of Product Innovation Management*, *32*(1), 138–153. https://doi.org/10.1111/jpim.12229

Urbinati, A., Chiaroni, D., Chiesa, V., & Frattini, F. (2020). The role of digital technologies in open innovation processes: an exploratory multiple case study analysis. *R&D Management*, *50*(1), 136–160. https://doi.org/10.1111/radm.12313

Usai, A., Fiano, F., Petruzzelli, A. M., Paoloni, P., Briamonte, M. F., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*, 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035

Wang, J., Wang, W., Liu, Y., & Wu, H. (2023). Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. *Technology in Society*, *72*, Article 102208. https://doi.org/10.1016/j.techsoc.2023.102208

Wang, L., Chen, Y., Ramsey, T. S., & Hewings, G. J. (2021). Will researching digital technology really empower green development? *Technology in Society*, *66*, Article 101638. https://doi.org/10.1016/j.techsoc.2021.101638

Wang, Q., & Zhang, F. (2020). Does increasing investment in research and development promote economic growth decoupling from carbon emission growth? An empirical analysis of BRICS countries. *Journal of Cleaner Production*, *252*, Article 119853. https://doi.org/10.1016/j.jclepro.2019.119853

Wen, H., Zhong, Q., & Lee, C. (2022). Digitalization, competition strategy and corporate innovation: Evidence from Chinese manufacturing listed companies. *International Review of Financial Analysis*, *82*, Article 102166. https://doi.org/10.1016/j.irfa.2022.102166

Woodard, C. J., Ramasubbu, N., Tschang, F. T., & Sambamurthy, V. (2013). Design capital and design moves: The logic of digital business strategy. *Mis Quarterly*, *37*(2), 537–564. https://doi.org/10.25300/MISQ/2013/37.2.10

Yadav, S., Samadhiya, A., Kumar, A., Majumdar, A., Garza-Reyes, J. A., & Luthra, S. (2023). Achieving the sustainable development goals through net zero emissions: Innovation-driven strategies for transitioning from incremental to radical lean, green and digital technologies. *Resources, Conservation and Recycling*, *197*, Article 107094. https://doi.org/10.1016/j.resconrec.2023.107094

Yang, C. (2022). How Artificial Intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy*, *51*(6), Article 104536. https://doi.org/10.1016/j.respol.2022.104536

Yang, Z., Gao, W., Han, Q., Qi, L., Cui, Y., & Chen, Y. (2022). Digitalization and carbon emissions: How does digital city construction affect china's carbon emission reduction? *Sustainable Cities and Society*, *87*, Article 104201. https://doi.org/10.1016/j.scs.2022.104201

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary – the new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Yu, H. C., & Tsai, B. Y. (2018). Environmental policy and sustainable development: An empirical study on carbon reduction among Chinese enterprises. *Corporate Social Responsibility and Environmental Management*, *25*(5), 1019–1026. https://doi.org/10.1002/csr.1499

Yu, L., Liu, Y., Niu, Y., & Xiao, Z. (2023). Greener together: The impact of China's mixed-ownership reform on firm carbon emissions. *Energy Policy*, *180*, Article 113689. https://doi.org/10.1016/j.enpol.2023.113689

Yu, L., Zhang, B., Yan, Z., & Cao, L. (2022). How do financing constraints enhance pollutant emissions intensity at enterprises? Evidence from microscopic data at the enterprise level in China. *Environmental Impact Assessment Review*, *96*, Aticle 106811. https://doi.org/10.1016/j.eiar.2022.106811

Yuan, H., Zou, L., & Feng, Y. (2023). How to achieve emission reduction without hindering economic growth? The role of judicial quality. *Ecological Economics*, *209*, Article 107839. https://doi.org/10.1016/j.ecolecon.2023.107839

Yuan, S., & Pan, X. (2023). The effects of digital technology application and supply chain management on corporate circular economy: A dynamic capability view. *Journal of Environmental Management*, *341*, Article 118082. https://doi.org/10.1016/j.jenvman.2023.118082

Zahra, S. A., Liu, W., & Si, S. (2023). How digital technology promotes entrepreneurship in ecosystems. *Technovation*, *119*, Article 102457. https://doi.org/10.1016/j.technovation.2022.102457

Zhang, F., Yang, B., & Zhu, L. (2023). Digital technology usage, strategic flexibility, and business model innovation in traditional manufacturing firms: The moderating role of the institutional environment. *Technological Forecasting and Social Change*, *194*, Article 122726. https://doi.org/10.1016/j.techfore.2023.122726

Zhang, S., Yu, Y., Kharrazi, A., Ren, H., & Ma, T. (2022). Quantifying the synergy and trade-offs among economy–energy–environment–social targets: A perspective of industrial restructuring. *Journal of Environmental Management*, *316*, Article 115285. https://doi.org/10.1016/j.jenvman.2022.115285

Zhang, W., Liu, X., Wang, D., & Zhou, J. (2022). Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy*, *165*, Article 112927. https://doi.org/10.1016/j.enpol.2022.112927

Zhang, Y., Xiaobo, L., & Mingqiang, X. (2021). Enterprise digital transformation and audit pricing. *Auditing Research*, (3), 62–71. (in Chinese)

Zheng, R., Wu, G., Cheng, Y., Liu, H., Wang, Y., & Wang, X. (2023). How does digitalization drive carbon emissions? The inverted U-shaped effect in China. *Environmental Impact Assessment Review*, *102*, Article 107203. https://doi.org/10.1016/j.eiar.2023.107203

Zhou, S., Zhou, P., & Ji, H. (2022). Can digital transformation alleviate corporate tax stickiness: The mediation effect of tax avoidance. *Technological Forecasting and Social Change*, *184*, Article 122028. https://doi.org/10.1016/j.techfore.2022.122028