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HOW BIG DATA DEVELOPMENT INFLUENCES ENTERPRISE GREEN TECHNOLOGY INNOVATION? THE MODERATING ROLE OF DIGITAL INCLUSIVE FINANCE

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Abstract. Existing research thoroughly discussed the dividend effect of big data development (BDD), but few analyses have been conducted from a micro perspective of enterprises' green development. With the exogenous policy shock of the National Big Data Comprehensive Pilot Zone, this study takes Chinese A-share listed companies as the research objects. We adopt the difference-in-differences model to systematically assess the impact of BDD on enterprise green technology innovation (GTI) and the moderating role played by digital inclusive finance (DIF) between the two. The study reveals that BDD significantly contributes to enterprise GTI. Furthermore, the facilitating effect of BDD on GTI is more significant in large enterprises, state-owned enterprises, enterprises with higher degrees of local government data openness, and enterprises with higher levels of the real economy. The moderating effect test shows that DIF significantly moderates BDD and enterprise GTI. Mechanism tests show that BDD promotes enterprise GTI through three channels: strengthening regional environmental regulation, alleviating enterprise financing constraints, and enhancing enterprise human capital. This paper provides valuable ideas for emerging economies planning to promote sustainable growth through BDD policies.

Keywords: big data development, green technology innovation, digital inclusive finance, National Big Data Comprehensive Pilot Zone, difference-in-differences model.

JEL Classification: O12, O25, O32.

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1. Introduction

To address development issues and cultivate development advantages, the Chinese government has adopted the new concept of "innovation, coordination, green, openness, and sharing." Green is the underlying hue of China's high-quality development, and it is required to meet the carbon neutrality and peaking targets (Huo et al., 2022). In December 2022, the NDRC and the MOST of China published a joint statement titled "Guiding Opinions on Further Improving the Market-Oriented Green Technology Innovation System" to promote green development. These perspectives indicate that green technology innovation (GTI) is emerging as a key driving force of green economic growth, and that the creation of an enterprise-oriented GTI framework must be accelerated. However, most firms now lack desire and skill in GTI (Zhang et al., 2023), and there is an urgent need to use the new momentum of green innovation.

The swift advancement of emerging technologies like big data, advanced algorithm and computing power, and large models has emerged as a pivotal catalyst for global economic transformation and advancement (Gan et al., 2023; Cheng et al., 2024). For a long time, the Chinese government places emphasis on the growth of big data, and futher officially designates its advancement as a national objective in 2015. Subsequently, the State Council released the Action Plan for Promoting the Development of Big Data, noting that big data has evolved into a novel impetus for economic transformation and growth, while advocating for its further development and integration into the real economy. In 2016, the NDRC gradually approved constructing eight national big data comprehensive pilot zones to promote the rapid and innovative development of big data. These zones included Guizhou Province, Henan Province, Shanghai Municipality, Inner Mongolia autonomous region, Chongqing Municipality, Shenyang Municipality, the Beijing–Tianjin–Hebei region, and the Pearl River Delta region (as shown in Figure 1). These eight pilot zones in the big data industry policy guidelines, top-level design, development goals, key tasks, and other pilot aspects build up China's big data development (BDD) practice of the "three-dimensional skeleton." Propelled by technological advancements and policy support, big data has emerged as a pivotal driver of China's economic transformation (Lin & Kunnathur, 2019). In this context, conducting an in-depth investigation of the influence of BDD on corporate GTI and its operational mechanisms holds significant theoretical and practical importance. It enables us to harness the full potential of big data's benefits and bolsters efforts towards sustainable development.

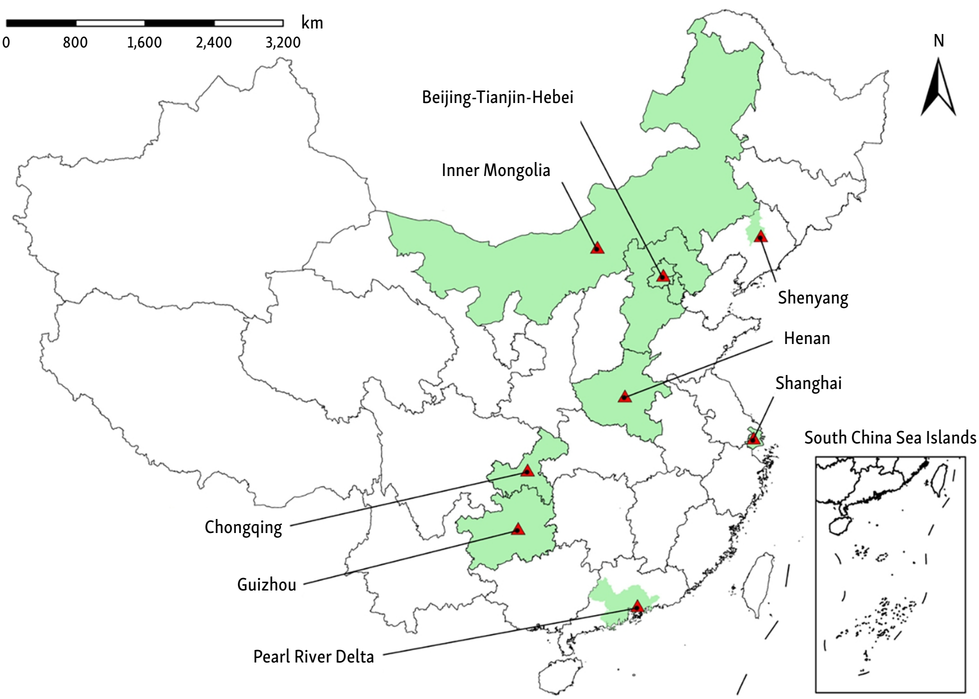

Figure 1. Geographical location of the National Big Data Comprehensive Pilot Zone

As a strategic factor of production leading a new round of global industrial revolution and technological change (Johnson et al., 2017), big data requires substantial financial support. As with most innovations, innovations in big data technologies or applications may face the risk of funding shortages and financing difficulties (Shin & Choi, 2015). In digitization, innovation agents also face greater losses when the innovation process is not adequately financed (Flyverbom et al., 2017), making the role of digital inclusive finance (DIF) increasingly important. In 2023, the State Council of China explicitly stated that financial institutions should improve their use of technology and vigorously develop inclusive finance through the application of new-generation information technologies like big data, cloud computing, large model and artificial intelligence. Furthermore, they claim that DIF is an important safeguard for incentivizing high-value innovations. Therefore, this paper further evaluates the role of DIF in the influence process of BDD on enterprise GTI. This approach provides valuable theoretical and practical implications for the government to better seize the new round of technological revolution and improve the financial inclusion system.

After systematically reviewing relevant literatures (Morrissey, 2020; Yang et al., 2020; Ferreira et al., 2023), we found that most scholars explore economic effects of BDD from a macro perspective, which pay close attention to economic growth, efficiency improvement, and innovation drive. Nonetheless, the influences of BDD on the microfirm level have received less attention (Wei et al., 2024). Some scholars discuss the role of the adoption of big data on improving green innovation capacity and efficiency based on microenterprise survey data (Waqas et al., 2021; Gao et al., 2023; Makhloufi, 2024). Unfortunately, there are few literature conducting empirical research on the intrinsic relationship between BDD and enterprise GTI based on a macroeconomic policy perspective.

The marginal contribution of this study is as follows. First, from the perspective of enterprise GTI, taking the big data pilot policy (BDPP) as an exogenous policy shock, we examine the effect of BDD and systematically explore its mechanism of action. This study further explores the impact mechanism of BDD on enterprise GTI from the perspectives of regional environmental regulation, enterprise financing constraints, and enterprise human capital. This exploration enriches the literature discussing the relationship between BDD and sustainable economic growth. Second, the BDD, DIF, and GTI are integrated into a unified theoretical framework to empirically test the moderating effect of DIF between BDD and enterprise GTI. This approach provides a valuable reference for the government to consturct the financial inclusion system related to emerging information technology. Third, based on the perspectives of both microenterprise characteristics and macroregional environments, we further distinguish the differences in enterprise scale, enterprise ownership, the degree of data openness of local governments and the level of the real economy. Furthermore, we investigate the heterogeneity of the effect of BDD on enterprises' GTI to provide valuable references for the government's precise policymaking.

2. Literature review

2.1. The impact of BDD

Policy documents and existing literature have defined big data more uniformly. The State Council points out that big data is a collection of data with huge volume and high application value and a new generation of information technology that collects, stores, correlates, and analyzes data. It has been well documented that data, technology, and applications are the three key elements of big data (Khan et al., 2022). The core of big data is to extract knowledge information from massive data rather than simple statistics of data (Corbett, 2018). Therefore, this study argues that BDD aims to extract knowledge information from massive data sets. Its core components include big data technologies used to process big data sets and the rapid and innovative development of big data applications.

With the rapid growth of big data, the breadth and depth of integrating big data with the real economy continue to grow, involving many fields and sectors, such as the economy, business, public administration, national security, and scientific research (Michael & Miller, 2013). Regarding the economic effects of BDD, most existing studies cut from the macro perspective, focusing on economic growth, efficiency improvement, and innovation drive. Regarding economic growth, Yang et al. (2020) systematically analyzed the critical role of big data in resource integration, scientific decision-making, and environmental regulation, concluding that big data can promote the development of a sustainable economy. Pappas et al. (2018) argued that big data could accelerate the flow of resources and optimize resource allocation, promoting economic growth. Regarding efficiency improvement, scholars agree that considerable value is hidden in the big data set, and the mining and development of massive data through big data technology can optimize resource allocation and improve productivity (Lichy et al., 2017). Ferreira et al. (2023) constructed a theoretical framework covering BDD, institutional environment, and governance efficiency, determining that BDD contributes to government governance efficiency and inhibits corrupt behavior through a practical fit with the institutional environment. Regarding innovation drive, Morrissey (2020) found that big data could create a new paradigm of management decision-making, improve enterprise management decision-making, and give enterprises the driving force of innovation. Can and Alatas (2017) argue that big data can transform production and research and development (R&D) models, driving technological innovation through its own "multiplier effect."

Nonetheless, the influences of BDD on the microfirm level have received less attention. The existing literature focuses on three aspects: enterprise innovation, enterprise value and enterprise total factor productivity. For instance, Bakker et al. (2020) specifically examined the effect of big data on firms' technological innovation capacity, arguing that big data could help firms enhance the search scope and efficiency for knowledge information and create new technologies by combining existing technologies through data analysis. Gao et al. (2023) found that the adoption of big data is benefitial for improving low-carbon innovation and green production of high-tech enterprises. Blazquez and Domenech (2018) found that big data applications could increase the market value of enterprises, and the mechanism of their impact lies in the fact that big data applications increase firms' productivity and R&D investment; however, insufficient related technology and talent may limit their positive impact. Gutmann et al. (2018) pointed out that BDD facilitates the enhancement of total factor productivity in the manufacturing industry, while firm innovation, factor allocation, and data empowerment can mediate this process. In addition, Waqas et al. (2021) and Makhloufi (2024) revealed that the cultivation of big data application and analysis capabilities will have a positive influence on green innovation efficiency and enterprise ESG performance through surveys of employees in manufacturing enterprises.

2.2. The influencing factors of GTI

Concerning the factors influencing enterprise GTI, the existing literature has discussed on the role of environmental regulation, intellectual property protection, and digital development. Numerous scholars have conducted research based on Porter's hypothesis (Du & Li, 2019; Peng et al., 2020; Wang et al., 2021), finding that both strong binding command-type environmental regulation and weak binding market-type and voluntary environmental regulation help promote enterprise GTI. Some scholars have also explored this based on the theory of externalities and found that intellectual property rights protection can effectively promote enterprise innovation (Lv et al., 2021). On this basis, Wang et al. (2023) divided intellectual property protection into three dimensions: legislative and regulatory protection, judicial protection, and administrative protection. They found that the role of judicial protection is the most important, that of legislative and regulatory protection is the second most important, and that the role of administrative protection is not yet clear. With the rapid development of the digital economy, digitization's impact on GTI has recently attracted attention from scholars. Zhao and Qian (2023) found that improving enterprise digitization levels could promote GTI in heavy-polluting enterprises; Hu et al. (2022) also found that regional digitization could promote GTI in resource-based enterprises. Xie et al. (2019a) concluded that enterprise digital transformation enhances the quantity of GTI and significantly improves the quality of GTI.

Scholars have carried out valuable discussions on the role of DIF in enterprise GTI. Research confirms that DIF facilitates GTI, mainly through channels such as alleviating financing constraints, reducing leverage levels, improving the efficiency of capital utilization, and enhancing the motivation of noncontrolling shareholders to participate in decision-making (Xie et al., 2019b; Liu et al., 2021). Ma et al. (2021) determined that the impact of DIF on enterprise green innovation exhibits increasing marginal effect characteristics. Li et al. (2018) empirically proved that DIF has a stronger innovation incentive effect on small- and medium-sized enterprises and private firms.

Existing studies have conducted valuable discussions around the impact of BDD on innovation behavior of microenterprises, but they have not explored the intrinsic relationship between BDD and enterprise GTI. Furthermore, the extant literature has neglected the role of DIF in the relationship between the two. As a significant driving force to promote economic transformation and development, it is particularly urgent to study the effect of BDD on enterprises' GTI during the critical period of sustainable economic growth. Thus, with the quasi-natural experiment of the BDPP and based on the panel data of Chinese A-share listed companies from 2010 to 2021, this paper incorporates BDD, DIF, and GTI into a unified theoretical framework. We systematically explore the effect of BDD on the enterprise GTI and its functioning mechanism and the moderating role of DIF in the two, which provide valuable decision-making references for better promotion of high-quality development.

3. Theoretical analysis and research hypothesis

3.1. The impact of BDD on GTI

The BDD may positively affect enterprise GTI. On one hand, big data can enhance the scope and efficiency of enterprise knowledge information search, help enterprises collect and develop fragmented information resources more efficiently (Wei, 2023), enable them to effectively access and utilize massive data and information, and improve their ability to refine innovation elements from existing information (Cui et al., 2022), thereby promoting enterprise GTI. On the other hand, big data technology facilitates enterprises in collecting consumers' historical information and exploring their potential needs (Saleem et al., 2021), thus facilitating the exchange of information between producers and consumers. Being oriented to consumer demand can help firms clarify the direction of R&D innovation and reduce uncertainty in the R&D process (Sahut et al., 2022). This orientation can effectively mitigate the factor mismatch among the supply and demand of R&D factors and the supply and demand of innovative products in the enterprise innovation system (Cammarano et al., 2023). Furthermore, the risk of commercialization failure of R&D and innovation results can be substantially reduced, the return rate of GTI output can be improved, and the enthusiasm for enterprises' GTI can be mobilized. Therefore, we propose the first Hypothesis:

H2: *The BDD can significantly promote enterprises' GTI.*

3.2. The moderating role of DIF

Technological innovation is an key driver of BDD (Xu et al., 2022). As a cutting-edge technology driving productivity change, the research and development process of big data technology requires enormous financial support from banks or securities firms. Due to the high uncertainty of technological revolution (Zhao et al., 2022), firms may face the risk of funding shortages and financing difficulties in cultivating new big data technologies. To obtain the dividends of new technologies and improve market competitiveness, some firms will continuously research and develop new technologies and apply them until a new market equilibrium is formed after the dividends of new technologies are exhausted (Fu et al., 2023). Therefore, if the financing channels of these enterprises are not effectively protected, it will be easy to trigger capital chain breaks and debt risks, limiting the innovation and development of big data technology.

DIF, as a key element of the inclusive financial system, is beneficial for reducing the threshold of financial services (Chen et al., 2022), improving the efficiency of enterprise financing (Wu & Wu, 2023), and reducing the intermediate cost of financing process (Sun & Tang, 2022), thus effectively relieving the issue of financing constraints faced by innovative enterprises. From the perspective of risk diversification, according to the resource-based theory (Sun & You, 2023), an enterprise's ability to acquire resources determines its responsiveness to the internal and the organization's external environment. DIF effectively improves financing efficiency and availability. It alleviates the financial mismatch problem (Liu et al., 2023), which significantly reduces the risk of enterprise innovation and prompts the management to be more willing to take a long-term perspective in making decisions on GTI.

Therefore, DIF can strengthen the financial support for enterprises' technological innovation process, which is beneficial for enterprises to release the great potential value of big data technology, which will positively affect GTI activities to a greater extent. In summary, the second Hypothesis is proposed:

H3: *DIF positively moderates the impact of BDD on enterprises' GTI.*

3.3. The influence mechanism of BDD on GTI

The influence mechanism of BDD on enterprise GTI can be classified as macro and micro levels. At the macromechanism level, BDD can influence enterprise GTI by strengthening regional environmental regulations. Environmental regulation is one of the key elements promoting enterprise GTI, and different types of environmental regulation can promote enterprise GTI, which many studies have verified centered on Porter's hypothesis (Wei et al., 2020; Lin & Ma, 2022). China's environmental information governance is currently characterized by environmental information dissemination dilemmas, such as insufficient information disclosure, environmental information distortion, and lack of feedback in information exchanges (Chen et al., 2023). In the face of redundant environmental information, it is difficult to deal with the current environmental governance problems under traditional management methods and resources, and big data can precisely solve this problem. Big data technology can rapidly integrate the fragmented environmental data information of different systems, departments, and enterprises, break the information dissemination barriers, and form a unified environmental data information system, which can help supervisory departments obtain high-value environmental data information promptly and help realize real-time and precise environmental supervision (Zheng & Zhang, 2023). Meanwhile, the application and popularization of big data technology is benefitial for improving the public's access to environmental information, enhancing the public's desire to take part in environmental information governance (Sun et al., 2021), and increasing the feedback mechanism for the public to supervise and report on environmental issues, thus improving the modern environmental governance system. The strengthening of environmental regulation and improving the environmental governance system are conducive to increasing the intensity of regional environmental regulation and promoting enterprise GTI.

The BDD can influence GTI at the micromechanism level by alleviating enterprises' financing constraints and enhancing their human capital. First, GTI is characterized by large upfront investment and a long payback cycle compared with traditional technological innovation. Therefore, it must be complemented by specific financial support to alleviate the potential problems of market mechanism that may confront in the R&D process (Sun et al., 2020), which also means that financing constraints are often the key obstacles faced by firms in the process of GTI. Furthermore, big data technology can mitigate enterprises' financing constraints by reducing the information asymmetry between financial institutions (such as banks and securities companies) and firms. With the help of big data technology, financial institutions can collect, categorize, and parse the fragmented massive information to better study the financial status of enterprises and reduce the information asymmetry between them and enterprises (Song et al., 2019). This approach can help financial institutions improve the efficiency of resource allocation and risk management ability, effectively avoid the issue of adverse selection in the financial market (Arzubiaga et al., 2021), and help enterprises accelerate the speed and efficiency of financing, reduce the intermediate cost of financing, and solve financial problems in the process of GTI, thereby providing convenient conditions for the development of enterprise GTI activities (Jum'a et al., 2023). Furthermore, the quality of the output of enterprise innovation activities depends on the level of human capital (Roth & Luczak-Roesch, 2020). The development of big data has led to the deep integration of big data technology with the production and operation activities of enterprises (Huang et al., 2018), thus stimulating the application of big data technology by enterprises and the demand for educated employees, prompting enterprises to enhance human capital. Self-innovation is achieved through learning, experience accumulation, and technology absorption, which promotes matching technology and skilled labor (Zhang et al., 2019). As the enterprise's human capital increases, the knowledge capital attached to high-quality human capital can be brought into enterprise's green and low-carbon innovation process. Furthermore, efficient exchanges will produce direct knowledge spillover and technology diffusion effects (Radicic & Petković, 2023), promoting enterprises' GTI. Figure 2 illustrates the impact mechanism of BDD on enterprises' GTI. In summary, the following three Hypotheses are proposed:

H3a: *The BDD can promote enterprises' GTI by strengthening regional environmental regulation.*

H3b: *The BDD can promote enterprises' GTI by alleviating enterprise financing constraints.*

H3c: *The BDD can promote enterprises' GTI by enhancing enterprise human capital.*

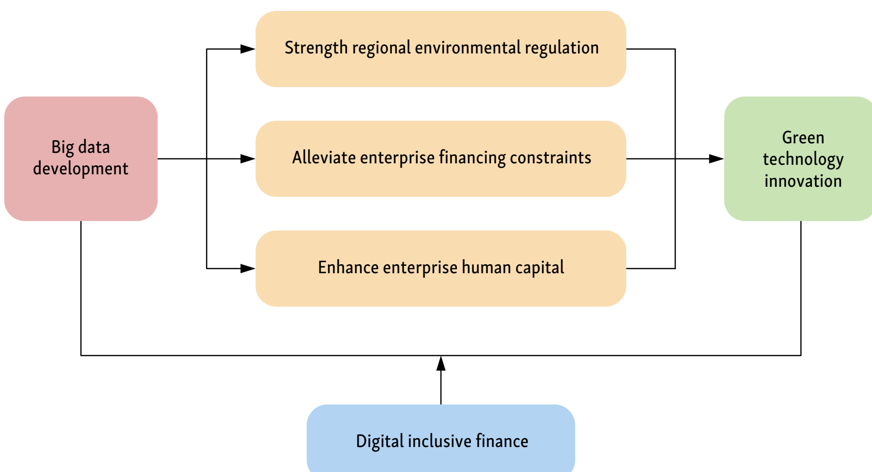

Figure 2. Mechanism analysis of BDD, DIF, and GTI

4. Empirical strategy

4.1. Empirical method

4.1.1. Benchmark model

This study uses the difference-in-differences (DID) model to assess the effect of the BDPP on enterprise GTI. The benchmark model is set as follows:

$$GTI_{it} = \beta_0 + \beta_1 Bigdata_{it} + \sum_{m=2}^{r+1} \beta_m Z_{m-1,it} + u_i + \xi_t + \nu_{it}. \quad (1)$$

where, *Bigdata* represents the dummy variable of the BDPP, satisfying $Bigdata_{it} = G_i \times T_{it}$, and β_1 reflects the policy effect. Z is the control variable vector, and r is the number of control variables (r = 9), m represents any integer from 2 to r + 1. u_i, ξ_t, and ν_{it} represent individual fixed effects, year fixed effects, and random disturbance terms, respectively.

4.1.2. Verification of transmission mechanism

Through mechanism analysis, we find that BDD may affect enterprise GTI by strengthening regional environmental regulation, alleviating financing constraints, and enhancing human capital for enterprises. We draw on the research of Baron and Kenny (1986) and construct the mediation model to verify the above effects. The verification of the transmission mechanism is divided into three steps.

Step 1: Verify the effect of the BDPP on enterprise GTI.

$$GTI_{it} = \beta_0 + \beta_1 Bigdata_{it} + \sum_{m=2}^{r+1} \beta_m Z_{m-1,it} + u_i + \xi_t + \nu_{it}. \quad (2)$$

Step 2: Verify the effect of the BDPP on the mediating variables.

$$M_{it} = \alpha_0 + \alpha_1 Bigdata_{it} + \sum_{m=2}^{r+1} \alpha_m Z_{m-1,it} + u_i + \xi_t + \nu_{it}. \quad (3)$$

Step 3: Verify the BDPP implementation and the impact of mediating variables on enterprise GTI.

$$GTI_{it} = \gamma_0 + \gamma_1 Bigdata_{it} + \gamma_2 M_{it} + \sum_{m=3}^{r+2} \gamma_m Z_{m-2,it} + u_i + \xi_t + \nu_{it}, \quad (4)$$

where, M_{it} denotes mediating variables, including regional environmental regulation, enterprise financing constraints, and enterprise human capital. If β_1 is significant with a lower estimated coefficient of γ_1, we conclude that the BDPP can promote enterprise GTI through mediating variables. The definitions of other variables and parameters are the same as in Equation (1).

4.1.3. Verification of moderating role

The moderating effect model is constructed to examine the moderating effect of DIF between the BDD and enterprise GTI.

$$GTI_{it} = \rho_0 + \rho_1 Bigdata_{it} + \rho_2 DIF_{it} + \rho_3 (Bigdata_{it} \times DIF_{it}) + \sum_{m=4}^{r+3} \rho_m Z_{m-2,it} + u_i + \xi_t + \nu_{it}, \quad (5)$$

where, ρ_3 is the coefficient of the interaction between the BDPP and DIF. If ρ_3 is significant and has the same sign as ρ_1, it indicates a positive regulatory effect. The definitions of other variables and parameters are the same as in Equation (1).

4.2. Variable selection

4.2.1. Green technology innovation

This article uses the natural logarithm of the number of enterprise green invention patent applications plus one to measure GTI (Lv et al., 2021). The selection criteria are as follows. First, the number of green invention patent applications intuitively reflects the output of GTI activities, with a high degree of quantification. Compared to green utility patents, it can better reflect high-level green innovation capabilities (Ma et al., 2021). Second, compared to patent authorization data, patent application data have stronger timeliness (Liu et al., 2021) and can promptly reflect the output of GTI activities.

4.2.2. Big data development

This article regards the BDPP as a quasi-natural experiment and serves as a measurement indicator for BDD. It is represented by the product of group dummy variable (G) and time dummy variable (T). Specifically, if the listed company i is located in the pilot area, the G_i value is 1; otherwise, the G_i value is 0. T_{it} takes a value of 1 during policy implementation (2016 and later) and 0 during nonpilot periods (before 2016). Therefore, if the listed company i is located in the pilot area and implements the pilot policy in year t, the $Bigdata_{it}$ value is 1; otherwise, the $Bigdata_{it}$ value is 0.

4.2.3. Mediating variables

To analyze the mechanism, we consider three factors: regional environmental regulation, enterprise financing constraints, and enterprise human capital. (1) We select the ratio of the completed investment in industrial pollution control in each province to the secondary industry's added value as the measurement indicator for regional environmental regulation (Sun & You, 2023). (2) Referring to Hadlock and Pierce (2010), we use the SA index to measure enterprises' financing constraints. A larger SA value indicates a more severe degree of financing constraints. (3) The percentage of employees with master's degrees and above in listed companies is used to measure enterprise human capital (Liu et al., 2023).

4.2.4. Moderating variables

This article uses the Peking University Digital Inclusive Finance Index as a proxy variable for DIF. It also uses the symmetrical and specific breakdown indicators of the breadth of coverage and depth of use of DIF for analysis (Sun & Tang, 2022) to ensure the reliability of the research findings.

4.2.5. Control variables

This paper further considers nine control variables to control the effect of other firm characteristics on GTI (Du & Li, 2019; Zhang et al., 2023; Chen et al., 2024;): enterprise size, enterprise age, asset–liability ratio, return on equity, Tobin Q index, number of board members, the proportion of independent directors, management fee ratio, and enterprise ownership. The control variables and their specific measures are shown in Table 1.

Table 1. Definitions of the main variables

Type	Variable	Abb	Definition
Explained variable	Green technology innovation	GTI	The natural logarithm of the number of green invention patent applications plus 1
Core explanatory variable	Big data development	Bigdata	Big data pilot policy
Mediating variable	Regional environmental regulation	Regul	The ratio of completed investment in industrial pollution control to the added value of the secondary industry
	Enterprise financing constraints	Finan	SA index
	Enterprise human capital	Human	The proportion of employees with a master's degree or above in listed companies
Moderating variable	Digital inclusive finance	DIF	Peking University Digital Inclusive Finance Index
Control variable	Enterprise size	Size	The natural logarithm of total assets at the end of the year
	Enterprise age	Age	The natural logarithm after adding 1 to the listing duration
	Asset–liability ratio	Lev	The ratio of year-end total liabilities to year-end total assets
	Return on equity	ROE	Net profit to owner's equity ratio
	Tobin Q index	TobinQ	The ratio of market value to capital replacement cost
	Number of board members	Board	The natural logarithm of the number of directors
	Proportion of independent directors	Indep	The ratio of the number of independent directors to the number of directors on the board of directors
	Management fee ratio	Mfee	The ratio of management expenses to operating income
	Enterprise Ownership	Owen	Whether it is a state-owned enterprise (1/0)

4.3. Data source

This paper selects Chinese A-share listed companies in 2010–2021 as the research sample. Data on green invention patent are from the Wind database (n.d.), data on enterprise characteristics are from the CSMAR database (n.d.), and data on regional characteristics are from the China Statistical Yearbook (National Bureau of Statistics of China, 2020). The raw data are preprocessed as follows. First, the samples of financial firms are excluded. Second, the samples of firms with ST, *ST, and PT are excluded. Third, a 1% bilateral tail reduction is applied to all continuous variables in the dataset. The descriptive statistics of the data are shown in Table 2.

Table 2. Descriptive statistics of variables

Variable	Abb	N	Mean	Std. dev	Min	Max
Green technology innovation	GTI	21670	3.746	2.008	0.327	46.045
Big data development	Bigdata	21670	0.087	0.283	0.000	1.000
Regional environmental regulation	Regul	21670	0.527	0.191	0.125	1.000
Enterprise financing constraints	Finan	21670	3.114	1.363	1.277	20.708
Enterprise human capital	Human	21670	0.253	0.304	0.227	1.000
Digital inclusive finance	DIF	21670	5.227	0.661	2.962	6.071
Enterprise size	Size	21670	22.312	1.280	20.008	25.966
Enterprise age	Age	21670	2.188	0.772	0.000	3.258
Asset–liability ratio	Lev	21670	0.425	0.204	0.056	0.867
Return on equity	ROE	21670	0.067	0.105	−0.448	0.321
Tobin Q index	TobinQ	21670	2.028	1.233	0.881	7.778
Number of board members	Board	21670	2.133	0.197	1.609	2.639
Proportion of independent directors	Indep	21670	0.376	0.054	0.333	0.571
Management fee ratio	Mfee	21670	0.094	0.073	0.010	0.425
Enterprise Ownership	Owen	21670	0.365	0.481	0.000	1.000

5. Empirical analysis

5.1. Baseline regression results

The estimation results of the benchmark regression model are shown in Table 3. Column (1) presents the result of not controlling for fixed effects and control variables, Column (2) is the result of controlling for time and firm fixed effects, and Columns (3)–(4) are the result of adding control variables to Columns (1)–(2), respectively. Columns (1)–(2) show that the regressions are highly significant whether we control for fixed effects. Columns (3)–(4) results show that the coefficients of the BDPP are still significantly positive at the 1% level after adding control variables, but the coefficients have decreased. This result indicates that other factors at the firm level affect GTI, and the selection of control variables in the model is valid. The full-variable regression result in Column (4) reveals that the BDPP increases the level of GTI of listed companies in the pilot region by 7.60% ($e^{0.0739}$ – 1) after removing possible confounding factors. This outcome indicates that BDD significantly promotes enterprises' GTI, which verifies Hypothesis 1.

5.2. Robustness test

5.2.1. Parallel trend test

The key premise of the DID model for evaluating BDPP is the fulfillment of the parallel trends assumption. Drawing on Beck et al. (2010), this paper uses the event study approach to conduct the test by including dummy variables in the regression model for the five years before and four years after the policy pilot. This approach verifies that the sample data satisfy the

Table 3. Benchmark regression results

Variables	(1)	(2)	(3)	(4)
Bigdata	0.3881*** (0.0217)	0.0862*** (0.0273)	0.1760*** (0.0221)	0.0739*** (0.0268)
Size			0.1962*** (0.0143)	0.1908*** (0.0157)
Age			0.0464*** (0.0025)	0.0421*** (0.0036)
Lev			0.0016 (0.0457)	0.0075 (0.0441)
ROE			0.0382** (0.0152)	0.0454*** (0.0159)
TobinQ			−0.0354* (0.0183)	−0.0338* (0.0181)
Board			0.0206 (0.0475)	0.0393 (0.0478)
Indep			−0.0319** (0.0143)	−0.0253* (0.0140)
Mfee			0.0421*** (0.0057)	0.0402*** (0.0051)
Owen			0.0514*** (0.0142)	0.0448*** (0.0135)
Constant	0.8060*** (0.1128)	0.4117*** (0.0233)	0.5296*** (0.0229)	0.4763*** (0.0190)
Year FE	NO	YES	NO	YES
Enterprise FE	NO	YES	NO	YES
N	21670	21670	21670	21670
R^2	0.1513	0.2191	0.2352	0.2494

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

parallel trends assumption based on the significance of the dummy variables. The model constructing for parallel trend test is as follows:

$$GTI_{it} = \beta_0 + \sum_{k=-6}^{4} \gamma_k D_{2016+k} + \sum_{m=2}^{r+1} \beta_m Z_{m-1,it} + \mu_i + \xi_t + \nu_{it}, \tag{6}$$

where D_{2016+k} denotes the interaction term with the dummy variable for the previous year, current year, and subsequent years of the BDPP. The one period before the treatment is selected as the base period. The description of other variables and parameters is the same as in Equation (1). Thus, γ_k denotes the policy effect in each event year. We determine whether the sample satisfies the parallel trend test by examining the significance of β_k. If $k \leq 0$, then β_k should not be significant and its confidence interval should contain 0. The short-dashed line in Figure 3 shows the confidence interval measured by a robust standard error at the 95% significance level.

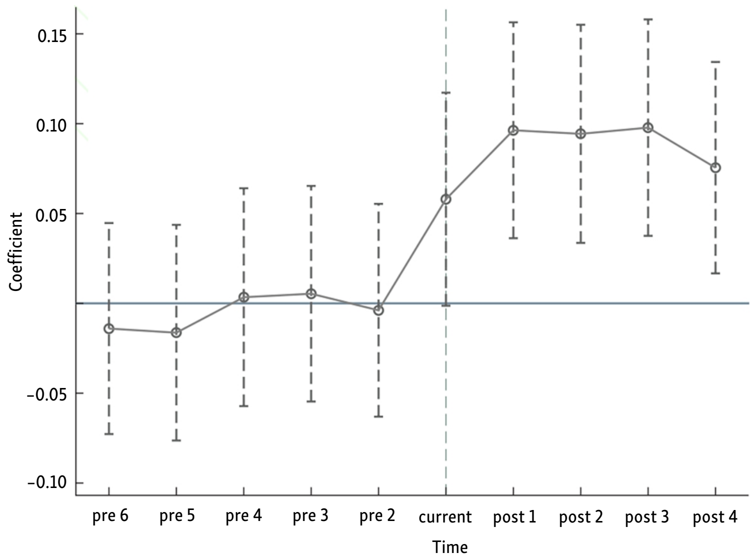

Figure 3. Parallel trend test

Figure 3 shows that the coefficient estimates prior to the BDPP are insignificant, suggesting that the GTI levels of enterprises in pilot and non-pilot areas were not significantly different before the pilot was launched, thereby passing the parallel trend test. The estimated coefficients for each period post-policy implementation are significantly above zero, indicating that the BDPP enhances enterprise GTI, with the policy's impact improving annually.

5.2.2. PSM-DID method

Different characteristics at the firm level may also affect GTI, which in turn interferes with the regression results. Therefore, the PSM-DID method is used to test the effect of BDD on GTI. Referring to Yuan (2023), the control variables in the benchmark model are used as matching variables, and then radius-matching method and kernel-matching method are used to match the samples of firms in the pilot area with the control group with the closest firm-level characteristics, respectively. Both PSM methods based on radius-matching method and kernel-matching method passed the balance test, based on which the DID model was utilized to regress the matched data and distill the net effect of the BDPP on GTI. The results of Columns (1)–(2) in Table 4 reveal that the estimated coefficients of the BDPP in the radius-matching and kernel-matching methods are all significantly positive at the 1% level. This result is consistent with the benchmark regression results in Table 3 and verifies the robustness of our findings.

5.2.3. Policy exogeneity test

The DID model requires that pilot and nonpilot districts cannot act before policy implementation because of the creation of practical expectations, i.e., the policy is theoretically exogenous. Drawing on Prasetyo (2024), the policy dummy variable, Bigdata_{b1} (which takes the value of 1 conditional on the district being a pilot district one year later), is added to the model to control for expected effects. The results of Column (3) in Table 4 reveal that the estimated coefficient on $Bigdata_{b1}$ is insignificant, and the estimated coefficient on $Bigdata_{b1}$ is significantly positive at the 5% level, suggesting that the expected effect of the BDPP does not exist, further validating the robustness of our findings.

5.2.4. Control regional characteristics

Both the level of regional economic development and Internet penetration may affect enterprise GTI (Peng et al., 2020). Therefore, the regression is rerun after adding gross domestic product per capita, Internet broadband access rate for users, broadband access port rate, and number of computers used per capita for each province as regional characteristic control variables. The Column (4) results in Table 4 reveal that the estimated coefficients for the BDPP are significantly positive, validating the robustness of the baseline regression results.

5.2.5. Exclude the impact of potential policies

Other green innovation policies may incentivize some pilot provinces and cities during the same period as the implementation of the BDPP. For example, the carbon emissions trading pilot policy was gradually launched in 2013, significantly promoting enterprises' GTI (Huang et al., 2022). Furthermore, the NDRC launched a large-scale pilot policy for low-carbon cities in 2012, which has been proven to be a significant promoter of enterprise GTI (Zhang et al., 2021). Furthermore, other innovation policies may affect some pilot areas, such as the pilot policy of building innovative cities promoted nationwide by the MOST and the NDRC in 2016. To exclude the effect of potential policies, we rerun the regressions with dummy variables for these three policies in the baseline model; the results are presented in Column (5) of Table 4. After controlling for the effects of other policy variables, the estimated coefficients of the BDPP remain significantly positive, indicating that BDD significantly promotes enterprise GTI, and the conclusion remains robust.

5.2.6. Replace the explained variable

The ratio of the number of green invention patent applications to the total number of invention patent applications is adopted as the indicator of enterprises' GTI. This indicator helps rule out confounding factors affecting green and invention patent applications (Lv et al., 2021). The Column (6) results in Table 4 show that the estimated coefficient for the BDPP is significantly positive at the 5% level. This result indicates that changing the measure of GTI does not affect the main findings.

5.3. Heterogeneity analysis

Further, this section examines the relationship between BDD and enterprise GTI from the perspectives of heterogeneity in microfirm characteristics and macroregional environment, respectively. The main question answered is whether the effect of BDD on GTI differs significantly according to enterprise scale, enterprise ownership, the degree of data openness of local government, and the level of the real economy.

Table 4. Robustness test results

Variables	(1) PSM-DID Radius matching	(2) PSM-DID Kernel matching	(3) Policy exogeneity test	(4) Control regional features	(5) Control relevant policies	(6) Replace explained variable
Bigdata	0.0731*** (0.0262)	0.0723*** (0.0264)	0.0595** (0.0276)	0.0590** (0.0309)	0.4271*** (0.1192)	0.0123** (0.0054)
$Bigdata_{b1}$			0.0207 (0.0268)			
Regional feature control variables				YES		
Relevant policy variables					YES	
Control variables	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES
N	21665	21657	21670	21670	21670	21670
R^2	0.2491	0.2472	0.2483	0.2334	0.2505	0.1346

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

5.3.1. Heterogeneity of enterprise scale

There may be differences in the effect of BDD on enterprises of different scales. Large enterprises have more capital, technology, and talent reserves than small enterprises. Big data technology can help large enterprises collect and analyze data information on capital, technology, and talent more quickly (Cammarano et al., 2023), efficiently integrate the resources needed for green innovation R&D activities, and improve the efficiency of green technology R&D, thus significantly promoting GTI. As a result, the role of BDD in facilitating GTI in large firms may be more prominent.

To verify the above logic, we divide the sample into large and small firms based on the median total assets of the firms, and grouped regressions are conducted. The results are presented in Columns (1)–(2) in Table 5. In the large enterprise group, the coefficient of the BDPP is significantly positive, indicating that BDD promotes the GTI of large enterprises. In contrast, in the small enterprise group, the coefficient of the BDPP is insignificant, indicating that BDD does not significantly promote small enterprises' GTI. The regression results are consistent with the theoretical analysis that the facilitating effect of BDD on GTI is more prominent in large enterprises.

5.3.2. Heterogeneity of enterprise ownership

Differences may also exist in the impact of BDDs on enterprises of different ownership. State-owned enterprises (SOEs) are influenced by local government and economic policies to a greater extent than nonSOEs (Luo et al., 2022). The BDPP is a top-down design formulated by the NDRC to develop big data, representing the direction of China's future development. SOEs will more actively implement the policy requirements to meet the national development demands. At the same time, SOEs receive more resources and policy support and are more capable of implementing BDD policies; therefore, the influence of BDD on GTI in SOEs may be more significant.

To verify the above inference, we divide the sample into SOEs and nonSOEs based on the type of firm ownership, and grouped regressions are conducted. The results in Columns (3)–(4) in Table 5 reveal that in SOEs and nonSOEs, BDD significantly promotes enterprise GTI; however, the Chow test on the coefficient difference between groups reveals that the promotion effect of BDD on SOEs is more significant than on nonSOEs. The regression results are consistent with the theoretical analysis that the promotion effect of BDD on GTI is more significant in SOEs.

5.3.3. Heterogeneity of data openness among local government

There may be differences in the effect of BDD on enterprise GTI in regions with different levels of local government data openness. The high-quality data resources held by local governments are vital in determining the ability of regional data and information integration and the allocation of data resources (Blazquez & Domenech, 2018). Regions with a high degree of data openness have more high-quality data available to enterprises through big data technology and a stronger ability to allocate innovation resources effectively. Enterprises in these regions have easy access to the knowledge and information resources needed for GTI, so they can efficiently carry out GTI activities; therefore, the facilitating effect of BDD on enterprise GTI may be more evident in regions with a high degree of local government data openness.

To verify the above inference, local governments' degree of data openness is classified according to the Digital Olympics index released by Fudan University (the first 25% is considered high, and the last 75% is considered low). The samples of enterprises are divided into two groups according to their locations to carry out the regression. The results of Columns (5)–(6) in Table 5 reveal that the impact of BDD on GTI is positive and significant for firms in highly open data areas. The BDD does not significantly impact GTI for firms in low open data areas. The regression results are consistent with the theoretical analysis; the promotion effect of BDD on enterprise GTI is more significant in regions with a high degree of local government data openness.

5.3.4. Heterogeneity of the real economy

There may also be differences in the effect of BDD on enterprise GTI in regions with different levels of the real economy development. The real economy centered on the manufacturing industry has created an external demand environment for the scale expansion and structural upgrading of big data industry. The development of various industries covered by the real economy lays a material foundation for the rapid advancement of big data (Sun et al., 2024). Enterprises in these regions with solid foundation of real economy will have easy access to the integration of digital economy and real economy, so they can efficiently carry out GTI activities. Therefore, the facilitating effect of BDD on enterprise GTI may be more evident in regions with a high level of the real economy.

We measure the development level of the real economy by the GDP after deducting the output value of the financial industry and real estate industry, and then divides the sample into two groups of strong and weak real economy by the median. The regression results are shown in columns (7) and (8) of Table 5. The results show that the effect of BDPP promoting enterprise GTI in regions with strong real economy is more significant. The economic reason is that regions with strong real economy have rich experience and material foundation in green innovation transformation. Therefore, they could make accumulated innovative achievements, understanding of manufacturing scenarios, and transformation experience and capability into general solutions, and combine them with the specific needs of enterprise GTI to solve the difficulties in a targeted way.

To further examine the existence of above heterogeneity effects, we construct dummy variables using grouping information and conduct cross-multiplier regression. Among them, set 1 for large enterprise group and 0 for small enterprise group; set 1 for SOE group and 0 for NonSOE group; set 1 for regions with a high degree of local government data openness and 0 for regions with a low degree of local government data openness; set 1 for regions with a high level of the real economy and 0 for regions with a low level of the real economy. The results in Table 6 are consistent with above conclusions, which indicates that the effect of BDD on enterprise GTI differs significantly according to enterprise scale, enterprise ownership, the degree of data openness of local government, and the level of the real economy.

Table 5. Heterogeneity analysis results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large	Small	SOEs	NonSOEs	High-opened	Low-opened	Strong real economy	Weak real economy
Bigdata	0.1031**	0.0194	0.0885**	0.0574*	0.0925**	0.0041	0.1008***	0.0597*
	(0.0462)	(0.0303)	(0.0441)	(0.0323)	(0.0376)	(0.0560)	(0.0274)	(0.0342)
Size	0.2133***	0.1561***	0.3023***	0.1032**	0.1837***	0.0969**	0.2004***	0.1103***
	(0.0204)	(0.0122)	(0.0254)	(0.0351)	(0.0148)	(0.0338)	(0.0245)	(0.0250)
Age	0.0725***	0.0322***	0.0401***	0.0550***	0.0449***	0.0417***	0.0522***	0.0413***
	(0.0136)	(0.0041)	(0.0032)	(0.0109)	(0.0070)	(0.0086)	(0.0126)	(0.0052)
Lev	0.0097	0.0279*	0.0456**	0.0078	0.0101*	0.0065	0.0090	0.0091
	(0.0218)	(0.0148)	(0.0137)	(0.0347)	(0.0102)	(0.0124)	(0.0420)	(0.0294)
ROE	0.0449**	0.0657***	0.1058***	0.0546***	0.0333**	0.0780***	0.0653***	0.0428***
	(0.0160)	(0.0176)	(0.0289)	(0.0105)	(0.0114)	(0.0223)	(0.0189)	(0.0166)
TobinQ	−0.0091	−0.0135	−0.0340*	−0.0304*	−0.046**	−0.0401**	−0.0287	−0.0335*
	(0.0122)	(0.0154)	(0.0191)	(0.0183)	(0.0155)	(0.0199)	(0.0302)	(0.0195)
Board	0.0363**	0.0403**	0.0319*	0.0302*	0.0556**	0.0498*	0.0685*	0.0304
	(0.0124)	(0.0192)	(0.0262)	(0.0242)	(0.0257)	(0.0377)	(0.0467)	(0.0376)
Indep	−0.0055	−0.0191*	−0.0353**	−0.0291*	−0.0088	−0.0076	−0.0148	−0.0365**
	(0.0146)	(0.0160)	(0.0134)	(0.0150)	(0.0139)	(0.0105)	(0.0149)	(0.0174)
Mfee	0.0337***	0.0429***	0.0235***	0.0559***	0.0491***	0.0404***	0.0607***	0.0393***
	(0.0078)	(0.0068)	(0.0046)	(0.0108)	(0.0092)	(0.0053)	(0.0114)	(0.0072)
Owen	0.0619***	0.0647***	0.0387***	0.0407***	0.0543***	0.0501***	0.0502***	0.0257**
	(0.0230)	(0.0226)	(0.0118)	(0.0136)	(0.0124)	(0.0112)	(0.0131)	(0.0136)
Constant	0.6831***	0.4455***	0.5990***	0.3455***	0.4705***	0.3369***	0.7881***	0.4893***
	(0.1092)	(0.0494)	(0.0981)	(0.0494)	(0.0646)	(0.0278)	(0.1293)	(0.0478)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES	YES	YES
N	9870	11800	7900	13770	12074	9596	8315	13355
R^2	0.2492	0.1563	0.2662	0.2403	0.2667	0.2280	0.2659	0.2571

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

Table 6. Cross-multiplier regression results

Variables	(1)	(2)	(3)	(4)
	Enterprise scale	Enterprise ownership	Data openness	Real economy
Bigdata	0.0520*** (0.0161)	0.0693*** (0.0172)	0.0885*** (0.0241)	0.0774*** (0.0221)
Bigdata × scale	0.1032*** (0.0208)			
Bigdata × ownership		0.0921*** (0.0188)		
Bigdata × data			0.0540*** (0.0138)	
Bigdata × real				0.0669*** (0.0150)
Control variables	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES
N	21670	21670	21670	21670
R^2	0.2381	0.2452	0.2551	0.2607

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

6. Moderating effect analysis

This Section utilizes a moderating effects model to test the moderating role of DIF between BDD and enterprise GTI. The Peking University Digital Inclusive Finance Index is used as a proxy variable for DIF, and the estimation result is shown in Column (1) in Table 7. DIF is also analyzed using the symmetrical and specific breakdown indicators of the breadth of coverage and depth of use of DIF, and the results are presented in Columns (2)–(3) in Table 7. The breadth of coverage focuses on the horizontal extension of financial services and products, reflecting the popularity of DIF; the depth of use focuses on the vertical extension, reflecting the actual utilization of DIF by the people.

The coefficients on the cross-multiplier terms of the BDPP and DIF (Bigdata × DIF) are all significantly positive at the 1% level, and replacing the measure of DIF did not affect the sign or significance of the coefficients. This finding implies that DIF positively moderates BDD's impact on enterprise GTI, and this finding is robust. Increasing the breadth of coverage and depth of use of DIF can enhance the financial support for enterprises' technological innovation process. This situation helps enterprises to release potential enormous value of big data technology, thus exerting a positive influence on GTI activities to a greater extent. In summary, Hypothesis 2 is verified.

Table 7. Moderating effect test results

Variables	(1) Total	(2) Coverage breadth	(3) Use depth
Bigdata	0.0878*** (0.0276)	0.0742*** (0.0261)	0.1763*** (0.0424)
DIF	0.1667*** (0.0415)	0.1630*** (0.0402)	0.1556*** (0.0345)
Bigdata × DIF	0.4374*** (0.1243)	0.3509*** (0.0818)	0.4508*** (0.1197)
Size	0.1801*** (0.0132)	0.1697*** (0.0256)	0.1408*** (0.0339)
Age	0.0315*** (0.0039)	0.0405*** (0.0074)	0.0521*** (0.0102)
Lev	0.0069 (0.0330)	0.0108 (0.0236)	0.0073 (0.0244)
ROE	0.0441*** (0.0132)	0.0595*** (0.0174)	0.0335** (0.0156)
TobinQ	−0.0273* (0.0174)	−0.0447** (0.0183)	−0.0387** (0.01728)
Board	0.0282 (0.0361)	0.0352* (0.0273)	0.0393* (0.0284)
Indep	−0.0231* (0.0160)	−0.0432** (0.0141)	−0.0358** (0.0165)
Mfee	0.0315*** (0.0068)	0.0207* (0.0096)	0.0236* (0.0157)
Owen	0.0334*** (0.0082)	0.0415*** (0.0124)	0.0249** (0.0090)
Constant	0.4528*** (0.0307)	0.4091*** (0.0213)	0.4834*** (0.0325)
Year FE	YES	YES	YES
Enterprise FE	YES	YES	YES
N	21670	21670	21670
R^2	0.2495	0.2283	0.2361

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

7. Mechanism verification

It has been verified that BDD can promote enterprise GTI, so what is the internal transmission mechanism of this process? Theoretical analysis shows that BDD may impact GTI by strengthening regional environmental regulation, alleviating enterprise financing constraints, and enhancing enterprise human capital. This section will empirically test this; the results are presented in Table 8.

First, the test of the mediating mechanism of regional environmental regulation is shown by the results of Columns (1)–(2). The coefficients of the BDPP are all significantly positive, while the coefficients of regional environmental regulation are also significantly positive.

Table 8. Intermediary mechanism test results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Regul	GTI	Finan	GTI	Human	GTI
	Regional environmental regulation		Enterprise financing constraints		Enterprise human capital	
Bigdata	0.0864*** (0.0056)	0.0593** (0.0273)	−0.0049*** (0.0012)	0.0558** (0.0267)	0.0041** (0.0022)	0.0671** (0.0302)
Regul		0.1482*** (0.0551)				
Finan				−4.8316*** (0.7675)		
Human						0.8693*** (0.2614)
Size	0.2101*** (0.0321)	0.1092*** (0.0140)	−0.0903*** (0.0054)	0.2105*** (0.0256)	0.0807*** (0.0058)	0.0860*** (0.0139)
Age	0.0537*** (0.0086)	0.0402*** (0.0050)	−0.0025*** (0.0014)	0.0533*** (0.0137)	0.0128*** (0.0032)	0.0380*** (0.0031)
Lev	0.0108 (0.0429)	0.0089 (0.0398)	−0.0013 (0.0046)	0.0090 (0.0431)	0.0023 (0.0042)	0.0064 (0.0305)
ROE	0.0563*** (0.0172)	0.0417*** (0.0155)	−0.0152*** (0.0051)	0.0664*** (0.0190)	0.0259*** (0.0078)	0.0396*** (0.0127)
TobinQ	−0.0445* (0.0214)	−0.0324* (0.0184)	0.0136* (0.0087)	−0.0298 (0.0309)	−0.0035* (0.0010)	−0.0552** (0.0271)
Board	0.0504* (0.0453)	0.0296 (0.0375)	−0.0192 (0.0173)	0.0696* (0.0487)	0.0094* (0.0075)	0.0196 (0.0283)
Indep	−0.0361* (0.0212)	−0.0354** (0.0163)	0.0157* (0.0146)	−0.0159 (0.0148)	−0.0057* (0.0042)	−0.0542** (0.0203)
Mfee	0.0514*** (0.0103)	0.0382*** (0.0061)	−0.0204*** (0.0053)	0.0608*** (0.0125)	0.0126*** (0.0037)	0.0317** (0.0091)
Owen	0.0557*** (0.0168)	0.0246** (0.0125)	−0.0149*** (0.0034)	0.0513*** (0.0142)	0.0110*** (0.0031)	0.0128* (0.0119)
Constant	0.5873*** (0.0391)	0.4620*** (0.0212)	0.1761*** (0.0083)	0.7892*** (0.1204)	0.2163*** (0.0145)	0.3154*** (0.0166)
Year FE	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES
N	21670	21670	21670	21670	21670	21670
R^2	0.3905	0.2526	0.6374	0.2583	0.2472	0.2431
Sobel test	Z = 8.696***		Z = −4.092***		Z = 13.347***	

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering at the city level is enclosed in parentheses.

This result suggests that BDD can strengthen regional environmental regulation, and the increase in the intensity of environmental regulation will significantly affect the enterprise's GTI. Second, the results in Columns (3)–(4) show the mediating mechanism test of enterprise financing constraints. The coefficient of the BDPP in Column (3) is significantly negative, indicating that the BDD significantly alleviates enterprise financing constraints; the coefficient of enterprise financing constraints in Column (4) is significantly negative, and the coefficient of the BDPP is significantly positive, indicating that the financing constraints display a part of the mediating effect. This finding implies that BDD promotes enterprise GTI output by alleviating their financing constraints. Finally, the results of Columns (5)–(6) show the mediation mechanism test of enterprise human capital. The regression coefficients of both the BDPP and enterprise human capital are significantly positive, indicating that BDD significantly optimizes the structure of enterprise human capital and that high-quality human capital provides sufficient talent and knowledge reserves for the enterprise's R&D activities, which in turn promotes the enterprise's GTI activities.

To further verified the mediating effect of regional environmental regulation, enterprise financing constraints and enterprise human capital, this study further adopt the bootstrap method for robustness check. The estimated results in Table 9 show that the 95% confidence intervals of mediating variables exclude zero, which means that regional environmental regulation, enterprise financing constraints, and enterprise human capital all play a mediating role in the impact of BDD on enterprise GTI. Therefore, Hypotheses 3a, 3b and 3c have been confirmed.

Table 9. Bootstrap mediation test results

Variables	Mediating effect	Effect	Boot SE	Boot LLCI	Boot ULCI
Regul	Indirect effect	0.0671	0.002	0.0334	0.1098
	Direct effect	0.1809	0.022	0.9011	0.4002
Finan	Indirect effect	−0.9205	0.005	−0.4116	−1.8865
	Direct effect	−2.7205	0.019	−1.3193	−5.0320
Human	Indirect effect	0.1560	0.003	0.7449	0.3055
	Direct effect	0.6091	0.034	0.3122	0.1357

8. Research conclusions and implications

8.1. Conclusions

With the help of a quasi-natural experiment of the BDPP, this article systematically evaluates the effect of BDD on enterprise GTI and the moderating role played by DIF between the two based on the data of Chinese A-share listed companies from 2010 to 2021 using the DID model. The study results reveal that (1) BDD significantly promotes GTI in enterprises. (2) Heterogeneity analysis indicates that the facilitating effect of BDD on GTI is more prominent among large enterprises, SOEs, enterprises with a higher degree of local government data openness, and enterprises with a higher level of the real economy. (3) The moderating effect test shows that DIF significantly moderates BDD and enterprise GTI. (4) The mechanism test shows that BDD mainly promotes enterprise GTI through three channels: strengthening regional environmental regulation, alleviating enterprise financing constraints, and enhancing enterprise human capital.

8.2. Policy implications

The core findings have policy implications for better releasing the dividend effect of BDD and promoting sustainable development. First, the government should use the BDPP to strengthen the institutional design of guiding enterprise GTI with BDD policies. Combining BDD planning with green development goals such as carbon peaking and carbon neutrality will release the potential dividend effect of BDD, thereby better promoting sustainable economic growth. Furthermore, the government should improve the construction of big data service platform, reduce the cost of enterprise information acquisition, improve the talent incentive and guarantee mechanism, improve the talent training and introduction policies, so as to meet the demand of scientific and technological talents for green innovation and development of enterprises.

Second, a long-term mechanism should be established to support enterprise GTI, emphasizing the role of big data technology in environmental protection, enterprise financing, and talent introduction. To formulate targeted supporting policies for the development of big data, deeply unblock the conduction channels for BDD to promote GTI in enterprises, and better promote green development through institutional safeguards. Moreover, the government should strengthen the construction of digital infrastructure, which is an important carrier of data elements. It is also need to improve the coverage of digital infrastructure represented by the Internet, actively promote digital technology innovation such as cloud computing and large models, and further release the GTI effect of big data.

Third, BDD policies should be refined to enhance relevance to different types of enterprises and regions. The government should increase its focus on small enterprises and nonSOEs and support the cultivation of big data technology innovation. The government should provide small-scale enterprises and non-SOEs with green innovation financial support, technical advice and other help to encourage them to actively apply big data for GTI, while strengthening the cooperation between enterprises and financial institutions, innovating and upgrading financial products and services, and easing the financing constraints of GTI of small-scale and non-SOEs. Meanwhile, it should insist on the wide availability of high-quality data for society and accelerate the application and development of big data in the production and operation of enterprises, thereby promoting the coordinated development of green and low-carbon innovation. The government can use big data technology to strengthen the supervision and management of green transformation of enterprises in heavy pollution industries, and formulate more detailed and accurate quality evaluation indicators of GTI, so as to encourage heavy pollution enterprises to carry out high-quality innovation.

Fourth, it is necessary to accelerate the construction of a DIF system and build an inclusive financial system encompassing digitization, breadth of coverage, and depth of use. Efforts will be made to enhance the popularization and practicality of DIF and to promote the horizontal and vertical extension of DIF. The government should actively guide financial institution to release the positive moderating role of DIF between BDD and enterprise GTI, promoting green and sustainable development. The government should promote the construction of digital credit system, integrate enterprises' data of GTI, improve enterprise credit, promote the banking industry to use big data technology to improve financing risk assessment, thereby relieving the financing constraints in the process of enterprise GTI.

8.3. Future directions

Last but not least, some limitations of this work also set paths for future research. First, this article assesses with the help of the exogenous shock of the BDPP. Due to the rich connotation of big data, with the continuous expansion of data sources, more comprehensive quantitative indicators can be considered constructed from the dimensions of data, technology, and application to reflect the level of BDD. Second, while this paper utilizes microfirm-level data for its empirical study, empirical evidence at the macrocity level is also worth exploring. Finally, as big data increases the speed and efficiency of information exchange and knowledge dissemination, it increases spatial connectivity between regions, which can have important implications for GTI. Therefore, further applying spatial econometric models to control spatial effects related to GTI can make the empirical results more reliable.

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Author contributions

Kaiming Cheng: supervision, investigation, conceptualization, Shucheng Liu: writing, reviewing and editing, validation, methodology. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials

The datasets used or analysed during the current study are available from the corresponding author on reasonable request.

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