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Original Research Article

A study on the impact of digital economy on green technology innovation of enterprises

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ABSTRACT

With global economic transformation and environmental sustainability increasingly taking center stage, the role of digital economy (DE) becomes particularly critical in corporate green technology innovation (GTI). Based on the data of Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2020, this paper explores the interactive effects of DE and GTI, and the mechanism role of data resources (DR) in it, as well as conducts in-depth analyses for different regional and city characteristics. The main findings are as follows: first, DE significantly promotes the process of GTI. Second, from the perspective of regional differences, the promotion effect of DE on green technology innovation is particularly prominent in the eastern and central regions. And analyzed from the city level, its positive effect is most significant in the second-tier cities, but shows a negative effect in the fourth and fifth-tier cities. Further examined from the perspective of resource dependence, DE inhibits green technology innovation in resource-based cities, while showing a significant facilitating effect in non-resource-based cities. Third, DE can further promote green technology innovation by enhancing firms' DR. Fourth, the study reveals the threshold effect of DR in this relationship: when $DR < 2.5649$, *DE* presents an inhibitory effect on green technological innovation, while its promotional effect begins to appear when $2.5649 \leq DR < 4.2767$, and the promotional effect of DE on GTI becomes more obvious when $DR \geq 4.2767$.

Keywords: digital economy; green technology innovation; data resources; resource-based cities; threshold modeling

1. Introduction

In recent years, with the profound changes in the global socio-economic structure and mankind's pursuit of higher quality of life, green innovation and digital economy have gradually stood at the forefront of academic research and industrial development. Among them, green innovation is not only the upgrading and expansion of traditional innovation mode, but also the in-depth embodiment and practice of the concept of ecological civilization and sustainable development. It requires the integration of ecological and environmental protection concepts into the research and experimental development (R&D) and application of new products, equipment, processes, systems, practices and methods to ensure a harmonious and balanced development among economy, resources and environment.

In the macro-context of the global economy, digital economy and green innovation are showing an intertwined and convergent development. digital economy, as described by Tapscott[1], aims to utilize ICT to

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reshape the socio-economic structure to become more efficient and smarter. Meanwhile, green innovation is the pursuit of environmental sustainability in this digital context[2]. It focuses on the use of digital technologies to optimize resource allocation, improve energy efficiency, and reduce environmental pollution[3]. When we combine the two, a clear picture emerges: a new economic model that utilizes advanced technologies to promote efficient economic development while focusing on environmental protection. digital economy provides the technological means to enable the realization of green innovation concepts; and green innovation injects a sustainable direction into digital economy. Thus, the two are not separate concepts, but are mutually reinforcing and complementary.

In terms of research perspectives, Sun et al.[4] explore the relationship between digital economy and urban green technology innovation from the perspective of environmental information constraints using a provincial panel, He et al.[5] find that digital economy promotes green technology innovation by alleviating financing constraints from the perspective of financing constraints, and Ma and Zhu[6] focus on the structural perspective of human capital and delve deeper into the human capital role in the two. In terms of the transmission mechanism, the relationship between digital economy and green technological innovation is not simple. digital economy provides the necessary technological means for green innovation, while green innovation injects the direction of sustainability into digital economy. Hao et al.[3] emphasize how digital technology can be utilized to improve resource and energy efficiency and thus reduce environmental pollution, which demonstrates the mediating role of digital technology in promoting green innovation. In addition, Krishnan et al.[7] even delved into how digital economy can further promote green technology innovation by promoting digital government. In the study of the relationship between digital economy and green technology innovation, both linear and nonlinear relationships have attracted the attention of scholars. Dou and Gao's[8] study shows that there is a positive nonlinear relationship between the two. While Geng et al.[9] and Wang et al.[10] provided more details and evidence about this positive relationship. Especially in the context of heavily polluted industries, digital transformation of enterprises presents a significant promotion effect on green technology innovation. However, Zhou[11] presents a distinctive point of view, as his study shows an inverted U-shaped relationship between the degree of digitization of regions and green technology innovation. These findings are a reminder that despite the complexity and variability of the relationship between digital economy and green technological innovation, their interactions still have far-reaching implications for today's economic transformation and development. Taken together, the academic community has not yet reached a consensus on the intrinsic link between DE and green technological innovation, despite the rich insights provided by the existing literature.

First, from the perspective of research, existing studies exploring the relationship between digital economy and green technological innovation are based on provinces and prefectural cities, with little discussion at the enterprise level, especially in the context of multi-dimensional heterogeneous perspectives such as geographic location, city type and resource background. Second, in the research on the transmission mechanism of digital economy and green technology innovation, most of the studies are carried out from different paths such as environmental information constraints, financing constraints and human capital structure, ignoring the possible transmission paths of DR in enterprise development in the context of the digital era. Finally, studies on DE and green technology innovation have mainly focused on the linear or nonlinear relationship between them, while studies on the complex nonlinear relationship such as the possible dynamic threshold are still relatively insufficient. Based on this, this study focuses on the mechanism effect of DR and the possible nonlinear relationship between digital economy and green technology innovation based on the data of Chinese Shanghai and Shenzhen A-shares from 2011 to 2020.

The contributions of this paper are as follows: first, it enriches the related literature and theories. Against the backdrop of global economic transformation and environmental sustainability becoming a central issue, this study fills the gap in the literature on how digital economy affects green technology innovation, especially in the specific economic context of China. Second, the mechanistic relationship between digital economy and green technology innovation is explored in depth. Through empirical tests, this paper not only confirms the positive driving effect of digital economy on green technology innovation, but also further reveals the key mechanistic role of data resources in this process. Third, it provides a detailed geographical and city-level analysis. For the first time, this study provides an in-depth exploration of the geographic and urban differences in the impact of digital economy on green technological innovation, especially in the context of different city sizes and resource dependencies, and provides targeted recommendations for relevant policy formulation. Fourth, the mechanism of data resource's role is revealed. This study examines in detail the interactive effects between data resources and digital economy on the impact of green technology innovation. In particular, we found that when data resources reaches a specific threshold (2.5649), its joint effect with digital economy on green technology innovation is negatively significant, when 2.5649≤ digital economy <4.2767, digital economy positively promotes green technology innovation, and when data resources ≥4.2767, the promotional effect of digital economy on green technology innovation is more obvious. This provides insights into understanding the functionality of data resources and its importance in green technology innovation.

The next part of this paper is structured as follows: The second part systematically explores the theoretical links between digital economy and green technology innovation to provide theoretical support for the subsequent empirical analysis. Part III describes in detail the methodological framework of this study, including data sources, variable selection, and empirical strategies to ensure the rigor and reliability of the analysis. Part IV presents the main results of the empirical analyses and verifies their consistency through a variety of robustness tests. Part V synthesizes the main findings of the study, explores their implications for academic research and practice, and provides policy recommendations based on the main conclusions.

2. Mechanisms and assumptions

2.1. DE and GTI

In the field of economics, the quest to understand how DE contributes to GTI has focused primarily on the synergy between digital assets and traditional factors of production. Based on the Solow production function model, we know that the productivity of a firm depends on capital, labor, and technological progress[12]. Digital assets, as a new type of capital factor, exhibit non-competitive and scalable characteristics compared to traditional physical capital[13]. First, knowledge output in DE is strongly non-exclusive and non-competitive. This means that once a digital technology innovation is born, its knowledge spillover effect can quickly spread to other fields with very low marginal cost[14]. Especially in the field of green technology, this knowledge spillover provides unparalleled opportunities for technological innovation, which in turn accelerates the development and application of technology. Second, the characteristics of digital assets enable real-time and dynamic reconfiguration of economic resources, which significantly improves production efficiency. In this context, green technology innovations are able to utilize these resources to more precisely assess and adjust the environmental impacts of their production processes[15]. Furthermore, the promotion of DE actually optimizes the flow of information in the market, thus reducing information asymmetry and externalities. This provides clearer market signals for green technology innovations, which strengthens their economic motivation[16]. Finally, DE creates an open and collaborative innovation ecology for firms[17]. For example, the collaboration between banks and fintech companies through APIs (Application Programming Interfaces) allows for the seamless integration of banking services into non-banking applications, enhancing customer value and driving innovation in financial products. Different R&D entities can work closely together through the digital platform, thus shortening the green technology R&D cycle and increasing the success rate of its market application. In summary, DE creates strong incentives and conditions for green technology innovation through multiple economic mechanisms and paths. This will further promote enterprises to invest more resources in green innovation, thus realizing higher economic and environmental benefits. In summary, this paper proposes the following hypothesis 1: DE can positively promote GTI.

2.2. Effects of DE on GTI heterogeneity

2.2.1. urban location heterogeneity

In the modern economic system, DE, as a new type of economic growth engine, has a profound impact on various types of business activities. In particular, DE exerts locational heterogeneity on GTI in different geographical structures[18]. In order to understand this heterogeneity in depth, we need to explore the economic mechanism behind it in depth from the perspective of economics. First, due to their higher degree of economic development, eastern cities have formed a complete market system, a high degree of industrial agglomeration, and a sound financial market, which provide a good soil for DE[19]. In this environment, firms have easy access to information about green technologies and can respond more quickly to changes in the market, thus improving their green technology innovation capability[20]. At the same time, since consumers in these cities have higher awareness and acceptance of green products, enterprises are more motivated to innovate green technologies. Secondly, central cities are in the catching-up stage in their economic development. These cities are actively absorbing advanced experiences and trying to improve their technological content and market competitiveness[21]. DE provides the necessary technical support and market information for these firms, which enables these firms to carry out green technology innovation more effectively. However, for western cities, although the development of DE has also had a positive impact, its promotion of green technological innovation is relatively weak due to the limitations of geography, culture, and economic foundation. First, the economic foundation of western cities is weak and the market mechanism is not perfect, which leads to more uncertainties and risks faced by enterprises in the innovation process[22]. Second, due to the relatively low level of education and scientific research, firms in these cities have certain barriers in acquiring and absorbing new technologies. Overall, there should be significant locational heterogeneity in the promotion effect of DE on GTI. In eastern and central cities, DE produces more significant positive impacts due to the advantages of their economic, cultural and social environments. However, in western cities, the promotion effect of DE on green technology innovation is relatively weak due to various limiting factors. Based on the above inferences, this paper proposes Hypothesis 2: The promotion effect of DE on green technology innovation is more obvious in eastern and central cities.

2.2.2. Urban scale heterogeneity

Against the backdrop of DE's rapid development, its impact on GTI varies significantly among cities of different sizes. To explore the reasons behind it from an economic perspective, we can derive it based on three core elements: Market mechanism, resource allocation and consumer preference. First, for first-tier cities, although they have highly digitalized infrastructure and sufficient technological resources, they are also relatively competitive[23]. In this environment, firms tend to focus more on short-term competitive market advantages and immediate profitability, which may undermine their long-term investment in green technology innovation[24]. In addition, the high consumption level and increasing cost of living in first-tier cities may also affect consumers' preference and willingness to purchase green technology products. While in second-tier cities, the positive effect of DE on GTI is more significant due to its dual developmental advantages in economy and technology[6]. The economic activity of second-tier cities creates an equilibrium with their moderate level of market competition, providing firms with the right incentives to innovate[25]. At the same time, its relatively relaxed market environment and higher consumer acceptance of green technologies further promote firms' R&D and investment in this area. However, this trend reverses when we turn to Tier 4 and Tier 5 cities. These cities are less digitally developed, posing constraints on firms' technological innovation capabilities[26]. Due to the limited market size, firms are more inclined to satisfy existing demand rather than seeking innovation in green technologies. In addition, consumers' green awareness and purchasing power are relatively low, which further weakens firms' incentives for green technology innovation. Summarizing the above analysis, there is an obvious interactive effect between DE and city size, which affects GTI in different directions and degrees. Based on this, this paper proposes Hypothesis 3: The promotion effect of DE on GTI shows city size heterogeneity, specifically, it is significantly positive in the second-tier cities, but significantly negative in the fourth- and fifth-tier cities.

2.2.3. Heterogeneity of resource-based cities

In the context of DE, its promotion or inhibition of GTI may show significant heterogeneity between resource-based and non-resource-based cities. In order to explore this heterogeneity in depth, we need to develop theoretical derivations from three dimensions: economic structure, production factors and market mechanism. First, resource-based cities have a relatively homogeneous economic structure and industrial chain due to their long-term reliance on natural resource extraction[27]. This structure results in firms being more easily constrained by resource constraints when making innovation decisions. The development of DE should, in theory, bring new development opportunities for such cities to break their resource dependence. However, the chronic lag in digital infrastructure, talent pool, and technological R&D in these cities makes it difficult for firms to rapidly absorb and apply digital technologies. Therefore, although DE brings the possibility of green technological innovation to resource-based cities, in practice, it may instead increase the cost burden of enterprises, thus inhibiting the incentive for green innovation[28]. On the other hand, in non-resource cities, economic development is more diversified and balanced, with a better industrial structure, and they tend to have more mature digital infrastructure and technical talents[29]. This provides a broader space for technology application and market opportunities for enterprises. The development of DE can be better embedded in the production and operation of enterprises in such cities, providing them with efficient tools such as data analysis and market forecasting. This not only reduces the operating costs of enterprises, but also provides real-time feedback and optimization solutions in green technology development and application. Therefore, DE in non-resource-based cities is more likely to be a powerful driver for green technology innovation. In summary, the impact of DE on green technology innovation in resource-based and non-resource-based cities shows obvious polarity. This not only stems from the economic structure and resource endowment of the two types of cities, but is also closely related to their historical path dependency in the process of digital transformation. Based on this, this paper proposes Hypothesis 4: In resource-based cities, DE inhibits GTI, while in non-resource-based cities, DE positively promotes GTI.

2.3. Mediating effect of DR on DE affecting GTI

In the context of DE development, the mediating role of DR may become more and more significant in promoting GTI. In order to explore this in depth, this paper draws inferences from both the facilitating role of DE in corporate DR and the facilitating role of DR in GTI.

In the context of DE, enterprises are no longer faced with pure production problems, but how to extract valuable information from big data and then transform it into strategic decisions[30]. The core of DE lies in the efficient flow and application of data, and the ability to generate and integrate data has become a determining factor in the core competitiveness of enterprises[31]. Through technologies such as the Internet of Things (IoT), big data analytics, and cloud computing, enterprises can track the flow of data in real time throughout the supply chain, from which they can extract information with decision-making value for product design, production processes, and market strategies. Such information assets not only provide firms with immediate market feedback, but also help them gain insights into future trends, ensuring that they stay ahead of the curve in a highly dynamic market environment[32].

DR, on the other hand, plays an irreplaceable role in the path of green technology innovation. The problems that green technologies often have to solve are complex and involve the intersection of multiple disciplines and fields, which makes it difficult for traditional R&D methods to achieve breakthroughs[33]. However, with the help of big data analytics, companies can dig deeper into environmental data, material properties, production processes, etc., from which they can discover new R&D paths or optimize existing technologies[34]. For example, by analyzing a large amount of environmental data, companies can find the most suitable green materials and the best production process, thus reducing production costs and improving the environmental performance of products. In addition, DR can help firms better understand consumers' needs and perceptions of green products, thereby optimizing product design and increasing market acceptance[35]. Overall, by facilitating the accumulation of DR, DE provides companies with unprecedented innovation opportunities and resources. And in this process, DR becomes the core driving force of green technology innovation, which pushes enterprises to break through technological bottlenecks and meet the growing demand for green products in the market and society. This interrelated and mutually reinforcing relationship shows the deep connection between DE and green technology innovation, and also provides us with a new, data-driven green technology innovation framework. Based on the above analysis, this paper proposes Hypothesis 5: DE contributes to GTI by promoting DR and thus GTI.

2.4. Threshold effect of DR

In the era of DE, the importance of DR is increasing day by day, and its driving force for corporate innovation, especially green technology innovation, shows a complex non-linear relationship. From the theoretical framework of emerging economics, we can propose the following theoretical derivations: first, from the perspective of the theory of marginal effect of capital input and output, DR in the primary stage can be regarded as "incomplete capital". At this stage, even though enterprises have started to accumulate data, their marginal contribution to technological innovation is negative because their quantity and quality have not yet reached a certain standard. This may be due to the fact that the initial data investment leads to high fixed costs, which are not sufficiently offset by the value of this primary data[36]. Therefore, the effect of DR is negatively significant on green technology innovation when it is less than the first threshold. However, as DR grows, firms begin to enjoy the benefits of economies of scale. When the amount of DR grows beyond the first threshold but less than the second threshold, the marginal benefits of data become positive, and firms begin to effectively utilize the data for decision support and accelerate green technology R&D and innovation[37]. When DR grows further beyond the second threshold, this positive effect not only persists but may be enhanced. This can be explained from the perspective of knowledge economy: a large amount of DR provides firms with abundant information that helps them gain insights into market trends, customer needs, and technological advances, leading to more efficient and targeted green innovation strategies[38]. Therefore, this paper proposes the following hypothesis: there is a threshold role of DR in the effect of DE affecting GTI, and the relationship between DE and GTI is significantly negative when DR is smaller than the first threshold, significantly positive when DR is larger than the first threshold but smaller than the second threshold, and the positive facilitation of the relationship is more obvious when DR is larger than the second threshold.

3. Model construction and data description

3.1. Modeling

To investigate how DE acts on GTI, this study proposes model (1):

$$GTI_{i,t} = \alpha_0 + \alpha_1 DE_{i,t} + \sum Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \tag{1}$$

In model (1), *i* and *t* represent firms and years, respectively, and $GTI_{i,t}$ denotes the GTI, and $DE_{i,t}$ describes the level of DE, the $\sum Controls_{i,t}$ is the set of control variables, Year and Industry are year and industry fixed effects, and $\varepsilon_{i,t}$ represent the error term.

In order to better understand the mediating effect of DR, this paper constructs model (2) and model (3):

$$DR_{i,t} = \alpha_0 + \alpha_1 DE_{i,t} + \sum Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \tag{2}$$

$$GTI_{i,t} = \alpha_0 + \alpha_1 DR_{i,t} + \sum Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \tag{3}$$

Here, model (2) focuses on the role of DE on DR, while model (3) concentrates on how DR affects GTI.

Further, in order to explore how DR affects the relationship between DE and DE, we employ a dynamic threshold regression approach and present model (4):

$$GTI_{i,t} = u_i + DE_{i,t} I\left(DR_{i,t} \le \gamma_1\right) A_1 + Dig_{i,t} I\left(\gamma_1 \le DR_{i,t} \le \gamma_2\right) A_2 + DE_{i,t} I(DR_{i,t} \ge \gamma_2) A_3 + Bx_{\mathrm{it}} + \varepsilon_{it} \tag{4}$$

where $I(\cdot)$ denotes the indicator function; the parameter $DR_{i,t}$ characterizes the external threshold variables; *γ1* and *γ2* define different thresholds; A1, A2, A3 and B denote the model coefficients to be estimated; and other relevant variables are described later.

3.2. Description of variables and data sources

3.2.1. Explanatory variables

Enterprise green technology innovation (GTI): For the measurement of GTI, this paper integrates the complex relationship between innovation inputs and outputs of enterprises. In the study, the focus is mainly on the actual behavioral data of enterprises, rather than being limited to subjective questionnaires. Specifically, the inputs of green technological innovation are regarded as green R&D funding or staffing, while the corresponding outputs are manifested as the value-added of intangible assets, the accumulation of green patents, or the economic benefits generated by new products. Given the time lag between patent application and approval, this study uses green patent application as a proxy variable for GTI. In order to dig deeper into the impact of DE on various types of green technological innovations, we classify green invention applications as substantive green technological innovations (GTI1), meanwhile, green utility model applications are categorized as strategic green technological innovations (GTI2). Considering that the number of green patents filed by many enterprises is zero and the "thick-tailed" distribution characteristics, we implement the natural logarithmic transformation of adding one to the number of patents in order to realize a more accurate interpretation of the data.

Figure 1 provided provide an in-depth insight into the temporal distribution of various aspects of GTI and its evolution. First, GTI reveals significant distributional fluctuations in its presentation across years. Such fluctuations can be attributed to environmental policy adjustments, technological evolution, and shifting market demand at both macro and micro levels. In particular, in 2020, we observe a significant widening of the distribution of GTI, similar to that of 2018, which reflects the strategic heterogeneity of market players on green technology innovation. In contrast, the distributions in 2015 and 2017 are more compact, suggesting consistency in resource allocation and strategy choice among market players at that time. Going into 2020, certain firms may be able to capture both technological and market dividends by investing more in green technology innovation, while others may be relatively lagging behind due to capital, technological, or strategic constraints. This strategic divergence may be further amplified given the impact of the COVID-19 pandemic on the global economy. Moreover, the bimodal structure in 2016 may have provided us with an early signal of increased market heterogeneity, while 2020 further corroborates this observation. Once again, GTI1 exhibits a concentrated distributional profile in 2017 and 2018, which may be closely related to government incentives, technological standard-setting, or growing market demand for green products and services at that time. Finally, GTI2 exhibits a stable distribution across years, reflecting consistency in strategic innovation despite significant differences in firms' substantive innovation strategies, which may be consistent with market expectations, consumer tastes, and the competitive landscape within the industry. Considered together, these violin plots provide us with a picture of the evolution of firms' strategies and market responses in green technology innovation, which are closely related to the external environment, policy formulation, technological advances, and firms' internal strategic positioning.

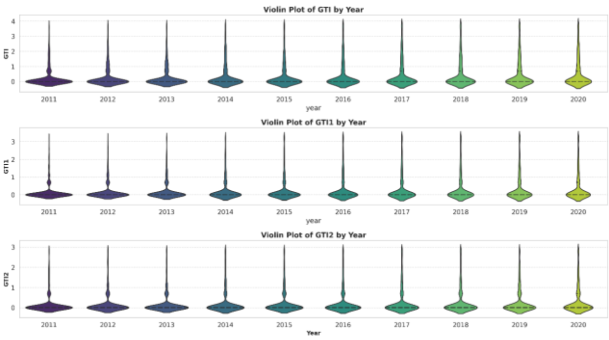

Figure 1. Violin diagram of the GTI.

3.2.2. Explanatory variables

Digital economy (DE): In the modern digitization-driven macroeconomic structure, DE has gradually shaped into a dominant variable affecting economic growth and urban evolution. In order to accurately capture its deep impact on the macroeconomy, this study combines city-level microdata with the two dimensions of Internet technology diffusion and digital finance popularization. First, in order to measure the depth and breadth of Internet technology diffusion in cities, we refer to the empirical research methodology of Huang et al.[39] and select Internet penetration rate, employee density in the IT sector, per capita telecommunication exchanges, and mobile expansion rate as the core indicators. These indicators are not only obtained from the China Urban Statistical Yearbook, but also present us with the integration and diffusion of Internet technology in the urban economic ecology. Further, for the evolution of digital finance, this study adopts the China Digital Inclusive Finance Indicator. This indicator is jointly constructed by Peking University's Institute of Digital Finance and Ant Financial Services Group, and is intended to capture the popularization and penetration of digital finance in the urban economy, further reflecting its externality effect on the macroeconomy. In summary, by standardizing these five key variables and weighing them comprehensively through principal component analysis and entropy method, we arrive at a composite index of DE development with explanatory power, i.e., DE and DE2, where DE serves as the main index and DE2 serves as the robustness test index.

3.2.3. Remaining variables

Mechanism variables: Data resources (DR): In order to explore the mechanism role of enterprise DR, this study chooses enterprise DE patent data as enterprise DR. To ensure the accuracy and consistency of the data, we refer to the Classification Reference Relationship table issued by the State Intellectual Property Office (SIPO). Based on this, we have finely constructed a framework of comparison between the International Patent Classification (IPC) and the Industry Classification, so as to ensure both the precise positioning of the industry and the accuracy and reliability of the patent data involved in the process of data processing and analysis. In order to further refine and standardize the metrics of DE patent data, we have performed a logarithmic transformation of the raw data after adding 1 to obtain more robust data distribution characteristics and ensure that the subsequent analysis is more statistically significant.

Figure 2 shows us the evolutionary trend of DR in three dimensions: time, size and volume. First, over time, we can observe a significant increase in DR, which may reflect the rapid development of DE and the increasing emphasis on data by organizations. This trend is consistent with the accelerating pace of global digitization and the growth of enterprise investments in data-driven decision making, artificial intelligence and machine learning. Second, in terms of DR size, most enterprises seem to have relatively medium-sized DRs, while only a few hold large amounts of data. This distribution may reveal the presence of data giants in the market, firms that have gained significant competitive advantage through data accumulation and network effects. However, it may also imply that small and medium-sized firms face challenges in accessing and utilizing data, i.e., the existence of "capital barriers". Finally, the distribution of the number of DRs suggests that there are a large number of firms with similar DR sizes for some years and data sizes, which may reflect a trend towards standardization or widespread adoption of technology in the industry. Overall, this figure provides valuable insights into the distribution and evolution of DR in DE, revealing the competitive landscape of the market, the impact of technological advancements, and the challenges and opportunities for firms in digital transformation.

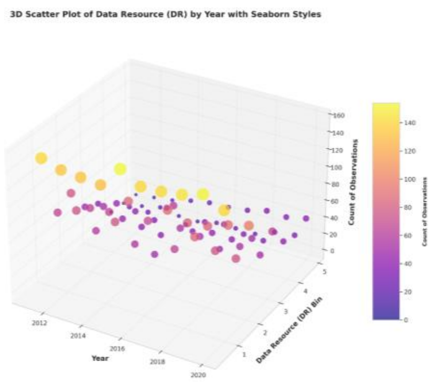

Figure 2. 3D scatter plot of DR.

Control variables: When assessing the factors influencing GTI, it is crucial to select appropriate control variables. Based on previous studies by Ma and Zhu[6] and Dou and Gao[40], we identified a series of factors that may have a significant impact. First, firm size (Size) is taken into account, as larger firms typically have richer resources and R&D budgets, but may also have more innovation barriers. Capital composition (Lev) concerns the firm's financing constraints and risk tolerance, while return on total assets (ROA) represents the managerial effectiveness of the firm and may be positively correlated with innovation activity. Corporate Growth Potential (Growth), on the other hand, reflects a company's propensity to seek new growth opportunities. The percentage of independent directors (Indep) may reflect the quality of corporate governance, while the shareholding of top ten shareholders (Top10) reveals the impact of shareholder concentration on corporate decision making. Tobin's Q (TobinQ) serves as the market's assessment of a firm's future opportunities and can be indicative of a firm's incentives to innovate. Structure of Ownership (SOE) takes into account the possible differences in strategic decisions between state-owned and private firms, while audits by the Big 4 audit firms (Big4) may represent the financial transparency and governance quality of the firms. To ensure the accuracy and robustness of the study, we also include year and industry fixed effects and use robust standard errors to control for possible heteroskedasticity issues.

3.3. Data sources and descriptive statistics of variables

Table 1 shows the descriptive statistics of the key variables. From the data of DE, the mean value is 1.157, which reflects that DE has been popularized and developed to a certain extent in the sample enterprises. Its standard deviation is 1.074, which indicates that there are large differences in the degree of DE among enterprises, which provides a basis for us to further analyze the relationship between DE and green technology innovation in different enterprises. For the overall green technology innovation (GTI), its mean is 0.408 and standard deviation is 0.815, indicating that there is a certain degree of green technology innovation activities in the enterprises within the sample, but there is still much room for improvement. Further subdividing into green technology substantive innovation (GTI1) and strategic innovation (GTI2), it can be found that the mean value of GTI1 is 0.273 and that of GTI2 is 0.246, which implies that among these two types of green technology innovations, there are slightly more substantive innovations than strategic innovations. However, the standard deviations of both show significant differences in green technology innovation activities among firms. When the control variables are taken into account, the top ten shareholders' ownership (Top10) averages 0.590, which implies that in these firms, equity is more concentrated. The mean value of the ownership structure (SOE) is 0.325, which implies that nearly one-third of the sample firms are state-owned enterprises. The proportion of audits by Big 4 audit firms (Big4), on the other hand, is lower, with an average of 0.0410, suggesting that most of the enterprises are not audited by Big 4 audit firms.

Table 1. Descriptive statistics of key variables.

Variable	N	Mean	SD	Min	Max.
GTI	19,658	0.408	0.815	0	3.714
GTI1	19,658	0.273	0.642	0	3.219
GTI2	19,658	0.246	0.584	0	2.833
DE	19,658	1.157	1.074	0.234	5.635
Size	19,658	22.09	1.213	19.91	25.68
Lev	19,658	0.413	0.204	0.0518	0.892
ROA	19,658	0.0447	0.0625	−0.221	0.223
Growth	19,658	0.161	0.374	−0.520	2.327
Top10	19,658	0.590	0.150	0.234	0.895
TobinQ	19,658	1.958	1.273	0	8.321
SOE	19,658	0.325	0.468	0	1
Big4	19,658	0.0410	0.198	0	1

4. Empirical analysis

4.1. Baseline regression results and discussion

From the baseline regression results in **Table 2**, we can clearly observe a significant positive relationship between DE and firms' green technology innovation (GTI and its two sub-indicators GTI1 and GTI2). Specifically, the coefficients of DE with GTI, GTI1, and GTI2 are 0.0394, 0.0274, and 0.0267, respectively, and show a positive relationship at the 1% significance level, which provides us with sufficient evidence that the development of DE plays a positive role in promoting both the overall GTI and its two sub-dimensions. Further looking at the other control variables, we can find that firm size (Size), capital structure (Lev) and return on total assets (ROA) all have a significant positive relationship with GTI, GTI1 and GTI2 at the 1% significance level. This implies that firms with larger firm size, higher financial leverage and higher return on total assets are more likely to engage in green technology innovation. In contrast, firms' growth potential

(Growth) and top ten shareholders' shareholding (Top10) have a significant negative relationship with all green technology innovation indicators, suggesting that these two factors may have a constraining effect on green technology innovation. Tobin's Q (TobinQ) showed a positive relationship at the 1% significance level for GTI1, but no significant effect for GTI2. This implies that the market valuation of firms may only have a positive effect on substantive green technology innovation. And the ownership structure (SOE) shows a positive relationship with GTI1 but a negative relationship with GTI2, implying that SOEs are more likely to engage in substantive green technological innovations and may have a relatively negative attitude towards strategic green technological innovations. In addition, whether or not they are audited by a "Big 4" accounting firm (Big4) has a significant positive relationship with all green technology innovation indicators, suggesting that high quality external audits may provide additional motivation for GTI. In summary, DE clearly provides a strong driving effect for GTI. Other firm characteristics, such as firm size, financial structure, market valuation, ownership structure, and the quality of external audits, on the other hand, influence GTI activities to varying degrees.

Table 2. Results of the benchmark regression.

Variables	**(1) GTI**	**(2) GTI1**	**(3) GTI2**
DE	0.0394***	0.0274***	0.0267***
	(6.2376)	(5.2779)	(5.9252)
Size	0.1742***	0.1450***	0.1017***
	(24.3321)	(24.4148)	(19.2051)
Lev	0.1439***	0.0718***	0.1169***
	(4.2567)	(2.6881)	(4.7763)
ROA	0.8034***	0.5708***	0.4646***
	(8.5369)	(7.6297)	(6.7685)
Growth	−0.0695***	−0.0502***	−0.0431***
	(−5.3863)	(−4.9013)	(−4.6729)
Top10	−0.2270***	−0.2087***	−0.0699**
	(−5.9711)	(−6.8572)	(−2.5455)
TobinQ	0.0073*	0.0135***	−0.0002
	(1.6761)	(3.8074)	(−0.0508)
SOE	0.0206	0.0432***	−0.0185*
	(1.5003)	(3.8491)	(−1.8991)
Big4	0.2405***	0.2190***	0.1511***
	(6.1685)	(6.6233)	(5.1624)
Constant	−3.4674***	−2.9357***	−2.0527***
	(−22.3902)	(−22.8917)	(−17.8316)
Year	Y	Y	Y
Industry	Y	Y	Y
Observations	19,658	19,658	19,658
R-squared	0.2240	0.2027	0.1858

4.2. Robustness and endogeneity tests

4.2.1 Robustness tests

The robustness tests in **Table 3** further strengthen our previous finding that DE has a positive impact on

GTI. This robustness test employs two different strategies to verify the robustness of the main regression results. First, columns (1) through (3) use a proxy variable for DE, DE2, to replace the original DE variable, DE. From the results, it is evident that there are significant positive relationships between DE2 and GTI, GTI1, and GTI2, and these relationships are confirmed at the 1% significance level. Specifically, the coefficients of DE2 on GTI, GTI1, and GTI2 are 0.0033, 0.0020, and 0.0025, respectively. These significance results indicate that our previous conclusions are still validated even when using the alternative metric of DE.

Table 3. Results of robustness tests.

Variables	**(1) GTI**	**(2) GTI1**	**(3) GTI2**	**(4) GTI**	**(5) GTI1**	**(6) GTI2**
DE2	0.0033***	0.0020***	0.0025***	-	-	-
	(4.8796)	(3.6364)	(5.1279)	-	-	-
L.DE	-	-	-	0.0321***	0.0217***	0.0234***
	-	-	-	(4.8740)	(4.0208)	(4.9494)
Controls	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y
Constant	−3.6504***	−3.0449***	−2.1936***	−3.5941***	−3.0717***	−2.1224***
	(−22.6318)	(−22.6260)	(−18.3789)	(−20.9074)	(−21.5095)	(−16.6809)
Observations	19,658	19,658	19,658	16,734	16,734	16,734
R-squared	0.2234	0.2021	0.1855	0.2304	0.2116	0.1904

Columns (4) through (6) To further ensure that our results are not due to time-related bias or possible reverse causality, we use the lagged one-period variable L.DE for DE as an explanatory variable. From the results in these columns, the relationship between lagged one-period DE and GTI, GTI1 and GTI2 remains positive at the 1% significance level. In particular, the coefficients of L.DE on GTI, GTI1, and GTI2 are 0.0321, 0.0217, and 0.0234, respectively. This further supports our original findings by demonstrating that the positive relationship between DE and GTI is robust over the time series.

Overall, whether we use the proxy variable DE2 or the lagged variable L.DE, our results strongly support the notion that DE positively contributes to GTI. Combined with the previous analysis, this provides us with even more solid evidence of a durable and robust positive relationship between DE and green technology innovation.

4.2.2. Endogeneity test

In economics research, in order to address possible endogeneity, instrumental variable method regression using appropriate instrumental variables is a common strategy. In this paper, in order to deal with the possible endogeneity of DE on GTI, we have chosen two instrumental variables. First, lagged 1-period DE (L.DE): According to Wooldridge[41], we consider that firms' behavior in the current period may be influenced by DE in the previous period. Therefore, it is reasonable to use one-period lagged DE as an instrumental variable because it is unlikely to be correlated with the current error term, thus satisfying the exogeneity condition for instrumental variables. Second, topographic relief degree (DXQFD): With reference to Lin and Tan[42], the topographic relief degree of each prefecture-level city is chosen as another instrumental variable. The degree of terrain undulation may affect the DE development of a region, for example, an area with complex terrain may have restrictions on the construction of communication and transportation infrastructure. However, the direct link with GTI in the current period is weak, so it is also a potentially strong instrumental variable.

As shown in **Table 4**, in Column (1), we see that the relationship between L.DE and DE is significantly positive at the 1% significance level with a coefficient of 0.7803, which indicates that L.DE is indeed correlated with DE and therefore satisfies the correlation condition for the instrumental variable. And in column (2), after the 2SLS regression using L.DE as an instrumental variable, the coefficient of DE on GTI is 0.0411, which is significantly positive at the 1% significance level, which further confirms our main finding. In Column (3), the coefficient of DXQFD on DE is −0.1478, which is significantly negative at the 1% significance level, indicating that terrain relief exhibits a significant negative association with DE development. However, in Column (4), when DXQFD is used as an instrumental variable, the effect of DE on GTI is still significantly positive with a coefficient of 0.2398 at the 1% significance level, which further supports the positive effect of DE on GTI. In summary, the results of the endogeneity test strongly support the positive impact of DE on GTI, whether using DE lagged by one period or terrain relief as an instrumental variable, thus confirming the robustness of our main findings.

Table 4. Results of endogeneity test.

Variables	**(1) DE**	**(2) GTI**	**(3) DE**	**(4) GTI**
L.DE	0.7803***	-	-	-
	(87.4758)	-	-	-
DE	-	0.0411***	-	0.2398***
	-	(5.1372)	-	(3.5491)
DXQFD	-	-	−0.1478***	-
	-	-	(−19.2121)	-
Controls	Y	Y	Y	Y
Year	Y	Y	Y	Y
Industry	Y	Y	Y	Y
Constant	0.2519***	-	1.0555***	-
	(3.1712)	-	(6.9764)	-
Observations	16,734	16,734	19,658	19,658
R-squared	0.8369	0.0885	0.3740	0.0338

4.3. Heterogeneity analysis

4.3.1. Urban location and scale heterogeneity

In **Table 5**, we first observe that DE exhibits significant heterogeneity across urban locations for green technology innovation. In the more economically developed eastern region, DE has a significant positive effect on GTI, with a coefficient of 0.0446, which is significant at the 1% level. In the central region, this positive effect is even more significant, with a coefficient of 0.1336. This implies that with the development of DE, firms in the central region may have higher growth potential in green technology innovation than in the eastern region. However, in the western region, although the coefficient of DE is 0.0199, its effect is not significant, implying that in relatively less economically developed regions, the promotion effect of DE on green technological innovation may be somehow constrained or delayed.

Further from the perspective of city size, the impact of DE on green technology innovation in cities of different sizes also shows significant heterogeneity. In the first-tier cities, the impact of DE on green technology innovation is not obvious, and its coefficient is almost zero and insignificant. While in second-tier cities, DE has a significant positive contribution to green technology innovation, with a coefficient of 0.1383 and significant at the 1% level. However, it is worth noting that as the city size decreases to the fourth and fifth tier cities, the effect of DE on green technology innovation is negative and significant, especially in the fifth-tier cities, where the coefficient reaches −0.7075. This may imply that in the smaller cities, the over-rapid development of DE may have some kind of suppressing or substituting effect on green technology innovation. Overall, these results reveal a strong relationship between DE development and geographic location and city size, further emphasizing the importance of targeted policies to promote green technology innovation.

Table 5. Regression results of city location and size heterogeneity.

	City location			**City scale**				
	The east	**Central section**	**Western part**	**Frontline**	**Second-tier**	**Third line**	**Four-line**	**Five-line**
Variables	GTI	GTI	GTI	GTI	GTI	GTI	GTI	GTI
DE	0.0446***	0.1336***	0.0199	−0.0002	0.1383***	0.0091	−0.1315*	−0.7075**
	(6.3357)	(2.7319)	(0.6664)	(−0.0105)	(7.1520)	(0.3732)	(−1.6889)	(−2.5617)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y	Y	Y	Y
Constant	−3.6098***	−3.5464***	−2.7944***	−3.8642***	−2.8387***	−4.4145***	−2.7866***	−1.3613
	(−17.6277)	(−8.7842)	(−7.7988)	(−8.3493)	(−11.0836)	(−16.6808)	(−7.1831)	(−0.7681)
Observations	12,514	3410	2646	2792	7475	7159	2050	173
R-squared	0.2305	0.2835	0.2644	0.3111	0.2189	0.2858	0.1896	0.6654

4.3.2. Heterogeneity of resource-based cities

According to the regression results in **Table 6**, we can observe that the impact of DE on green technological innovation shows a significant difference between resource-based and non-resource-based cities. In resource-based cities, DE exhibits a negative impact on GTI with a coefficient of −0.3105, which is significant at the 1% level. This means that in these cities that depend on specific resources (e.g., minerals), the development of DE may have some kind of conflict or substitution effect with the existence of traditional industries, which may have a negative effect on green technology innovation. In contrast, in non-resource cities, DE has a significant positive effect on green technology innovation with a coefficient of 0.0409, again significant at the 1% level. This suggests that in these cities, as DE develops, firms are more likely to engage in green technology innovation. This result may reflect the fact that firms in non-resource-based cities are more likely to adopt new technologies and business models rather than rely on traditional resources. Taken together, these regression results reveal a strong relationship between DE development and the resource attributes of cities. Especially in resource-based cities, policymakers should pay close attention to the potential risks that may be associated with the rapid development of DE, in order to ensure that green technological innovation can be promoted and supported in a sustainable manner.

Table 6. Regression results of heterogeneity in resource cities.

	Resource-based city	
	Be	**Clogged**
Variables	**GTI**	**GTI**
DE	−0.3105***	0.0409***
	(−3.8794)	(6.2383)
Constant	−3.3645***	−3.3733***
	(−8.2732)	(−19.9857)

Table 6. (*Continued*).

	Resource-based city	
	Be	**Clogged**
Variables	**GTI**	**GTI**
Controls	Y	Y
Year	Y	Y
Industry	Y	Y
Observations	2489	17,165
R-squared	0.2628	0.2319

5. Analysis of the mediating effects of DR

Table 7 shows the results of the mediating variable regressions. First, we focus on the results in Column (1), where the facilitating effect of DE on DR is captured. The coefficient of DE is 0.0704, which is significant at the 1% level. This indicates that as DE develops, firms' access to and utilization of DR increases significantly. DE provides firms with richer data sources and applications, thus enhancing firms' data acquisition capabilities. This result highlights the positive association between DE and DR and confirms that DE brings more DR to the firms.

Second, we consider the regression results in columns (2), (3) and (4). In all three regressions, DR is significantly and positively associated with green technology innovation and its two sub-indicators (GTI1 and GTI2). Specifically, the coefficients of DR on GTI, GTI1, and GTI2 are 0.4122, 0.3119, and 0.2537, respectively, which are all significant at the 1% level. This implies that having more DR can significantly contribute to firms' green technology innovation and its related sub-indicators. This may be due to the fact that DR can help firms better understand environmental challenges and more accurately evaluate technological solutions, thus promoting green technology innovation more effectively.

Combining these results, we argue that DE further promotes firms' green technology innovation by enhancing the mediating effect of DR. This finding highlights the key role of DR in the relationship between DE and green technology innovation. Policymakers and business leaders should emphasize the development of DE and the accumulation of DR to better promote green technology innovation.

Table 7. Regression results for mediated effects.

Variables	**(1) DR**	**(2) GTI**	**(3) GTI1**	**(4) GTI2**
DE	0.0704***	-	-	-
	(7.9065)	-	-	-
DR	-	0.4122***	0.3119***	0.2537***
	-	(70.5032)	(60.3906)	(50.5904)
Controls	Y	Y	Y	Y
Year	Y	Y	Y	Y
Industry	Y	Y	Y	Y
Constant	−4.2929***	−1.6868***	−1.5910***	−0.9543***
	(−20.8158)	(−15.3058)	(−17.2682)	(−10.6628)
Observations	19,658	19,658	19,658	19,658
R-squared	0.3936	0.4709	0.4310	0.3676

6. Further analysis

Table 8 depicts the results of the DR threshold effect test. The table shows that DRs have a significant effect on the dependent variable under both single and double threshold conditions, as can be clearly seen from their F-statistics and corresponding p-values (which are much less than the 1% significance level). Specifically, when DRs reach a specific level, their effect on the dependent variable changes significantly. This change may occur again, when the DR reaches another significant level. However, we do not have enough evidence to support a three-threshold effect, as its corresponding *p*-value of 0.5233 suggests that there are not three independent significant thresholds in the current dataset.

Table 8. DR threshold effect test results.

Threshold	F	P	Number of BS	Threshold value		
				1%	5%	10%
Single	239.29	0.0000	300	19.9302	15.0845	11.0321
Double	107.17	0.0000	300	15.5861	11.5451	9.5905
Triple	33.64	0.5233	300	120.5460	106.0149	99.4190

Table 9 presents us with a complex relationship between DE and GTI depending on the different levels of DR. First, we notice that when the DR is relatively low (i.e., $DR < 2.5649$), there is a negative relationship between DE and GTI. This may imply that in the preliminary stage, firms may rely too much on data or digital tools, causing them to neglect the core elements of green technology innovation. Alternatively, preliminary digitization may have brought about some inefficiencies or waste of resources, thus inhibiting the development of green technologies. However, when DR reaches a moderate level (i.e., $2.5649 \leq DR < 4.2767$), we see a positive relationship between DE and GTI. At this stage, firms may begin to better integrate DR and digital tools, enabling them to focus more on green innovation. Digital tools such as data analytics and machine learning may provide firms with insights into market and technology trends at this stage, thus driving more sustained and effective green technology innovation. Finally, the positive impact of DE on GTI appears particularly strong when DR reaches a relatively high level (i.e., $DR \geq 4.2767$). This may indicate that a mature DE environment provides firms with more advanced data-driven decision-making tools and platforms that enable them to invest in green technology innovation in a more comprehensive and sustainable manner. This non-linear relationship reveals that the role played by DR at different stages may be variable. Understanding the nature and drivers of this variability is critical for policymakers and business decision makers, as it can help them develop more targeted strategies to maximize the potential benefits of DE while promoting green technology innovation in their firms.

Figure 3 shows the construction of confidence intervals for the threshold model of DR. First, looking at the LR statistic in the upper panel, we can see a clear "dip" at about 2.5, which coincides with the first threshold value for DR provided in **Table 9** ($DR < 2.5649$). Until this point, DR is negatively correlated for DE vs. GTI. Then, from 2.5 to about 4, the trend of the LR statistic is relatively stable, which may imply that its positive correlation with DE and GTI is also relatively stable within this DR range. This is consistent with the second interval in **Table 9** ($2.5649 \leq DR < 4.2767$). In the first figure, the LR statistic rises sharply when the threshold exceeds 4, which is consistent with the finding that the positive effect is most significant in the third interval of DR ($DR \geq 4.2767$) in **Table 9**. After this threshold, the accumulation of DR enhances the positive correlation between DE and GTI. For the lower panel, there is a significant drop in the LR statistic around 3.5, but it does not correspond directly to any particular interval in **Table 9**. A possible interpretation is that this represents a turning point or inflection point, meaning that at this point the positive impact of DR growth on GTI begins to diminish, but still remains positively correlated. The red dotted line represents the statistical significance limit, and both the top and bottom graphs show that the LR statistic exceeds this limit in most intervals, proving that the model's effect is statistically significant. Taken together, these graphs and tabular data reveal the different effects of DR on the DE-GTI relationship at different stages or levels. This nonlinear threshold effect emphasizes that at some specific levels of DR, its economic value and impact on green technology innovation can change significantly.

Table 9. Regressions and Tests for DR Threshold.

Variables	**Coef.**	**Std. Err**	***t***	***P* > |*t*|**
Size	0.1235***	0.017	7.37	0.000
Lev	−0.0493	0.067	−0.74	0.461
ROA	0.0935	0.123	0.76	0.446
Growth	−0.0379***	0.011	−3.41	0.001
Top10	−0.2807***	0.080	−3.51	0.000
TobinQ	0.0022	0.005	0.40	0.690
SOE	0.0401	0.043	0.93	0.352
Big4	−0.1068	0.069	−1.54	0.123
DR (*DR* < 2.5649)	−0.0431***	0.008	−5.37	0.000
DR (2.5649 ≤ *DR* < 4.2767)	0.0566***	0.019	2.97	0.003
DR (*DR* ≥ 4.2767)	0.2766***	0.047	5.83	0.000
cons	−2.1485***	0.374	−5.74	0.000

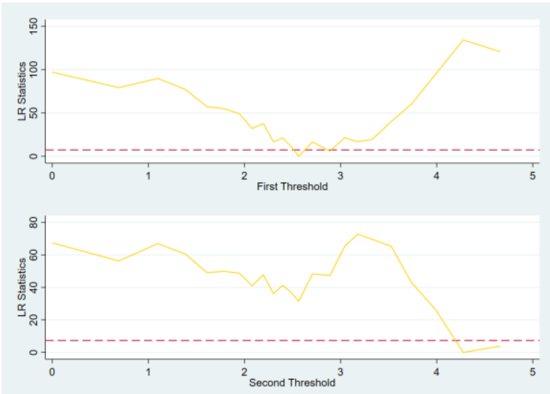

Figure 3. DR threshold regression graph.

7. Conclusions, recommendations and shortcomings

7.1. Conclusions of the study

Against the backdrop of continuous global economic transformation and the growing concern for environmental sustainability, DE has become an important engine for driving GTI. Drawing on empirical data from Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2020, this study explores in depth the complex relationship between DE and green technology innovation and analyzes how DR plays a key role in this process. First, the study confirms that DE provides firms with wider access to information and more efficient operational mechanisms, thus strongly contributing to green technology innovation. This hints at the great potential of digital technologies in promoting corporate sustainability. Second, from a geographical perspective, we observe that the positive impact of DE on green technology innovation is more pronounced in the eastern and central regions. This may be related to the more mature technological infrastructure and higher industrial concentration in these regions. However, the effect turns negative for Tier 4 and Tier 5 cities, possibly reflecting the lag in the digitization process in these regions and the influence of other locally specific factors. Deepening further from the perspective of resource dependence, we find that in resource-based cities, long-term dependence on traditional resources may make firms encounter greater resistance to transformation and innovation, leading to a limitation of the effect of DE. Comparatively, in non-resource-based cities, DE unleashes its potential driving force for green technology innovation. Third, DE not only promotes green technology innovation through direct technological transformation, but more importantly, it brings greater innovation space and opportunities for firms by empowering them and improving their DR. Finally, in the context of DE, the relationship between DR and GTI exhibits obvious nonlinear characteristics. Specifically, this relationship is affected by the threshold effect of DR, leading to its different dynamics at different DR levels. First, when DR is less than 2.5649, we observe that DE has an inhibitory effect on green technological innovation. From an economic perspective, this may be due to the fact that at this stage, firms are still initially exploring the application of data, and the quality and quantity of data may not be sufficient to support effective technological innovation. In addition, early data collection and management may impose additional costs that may outweigh the potential benefits of data-driven innovation, thus inhibiting innovation activities in green technologies in general. However, when the DR is between 2.5649 and 4.2767, DE begins to positively contribute to green technology innovation as the volume and quality of data increases. This may reflect the fact that firms are beginning to realize economies of scale and scope of data, allowing the marginal benefits of data to exceed its marginal costs. At this stage, firms may have established more sophisticated data management and analytics capabilities, enabling them to extract valuable information from their data more efficiently, thereby accelerating technological innovation. Finally, the boosting effect of DE on GTI becomes more pronounced when the DR exceeds 4.2767. This stage may represent the point at which DR reaches a "critical mass" where data not only provides a continuous flow of information to the enterprise, but also potentially spawns new opportunities for collaboration and innovation, facilitating cross-domain knowledge fusion and technology integration, thus further accelerating the rate of innovation in green technologies. In summary, the quantity and quality of DR have different impacts on green technology innovation at different stages, a phenomenon that reveals the complex interactions between DE and technological innovation and provides important insights for business decision makers and policymakers on how to maximize the value of data.

7.2. Policy recommendations

With the transformation of the global economy and the growing importance of environmental sustainability, the role of DE in promoting GTI is becoming increasingly critical. Based on the findings of the study, this paper offers strategic recommendations for governments: first, governments need to strengthen their investment in and construction of digital infrastructure. Especially in the eastern and central regions, such investment can significantly boost technological development and innovation. This will not only boost economic growth in these regions, but also improve the green technology innovation capacity of enterprises. Second, in response to the negative association between DE and green technology innovation demonstrated by Tier 4 and Tier 5 cities, the government should develop specific policies for these areas. This includes providing financial support to accelerate the digitization process in these cities, as well as providing training for local firms in digital technology application and innovation. Finally, given the disincentive effect that resource-based cities exhibit in DE and green technology innovation, governments should develop appropriate long-term transformation strategies. This means encouraging these cities to shift from over-reliance on traditional resources to a more sustainable, environmentally friendly, and digitized economic model, thereby ensuring their future economic robustness and sustainable growth. In summary, governments have many strategic options at the intersection of DE and green technology innovation. With appropriate policies and effective implementation, governments can ensure that both of these key areas are properly supported and promoted.

Based on the findings of this paper, enterprises should consider the following points when formulating future development strategies: first, enterprises should fully recognize the importance of DE in promoting green technology innovation, especially in the eastern and central regions. Enterprises should increase their investment in digital technologies, such as data analytics, artificial intelligence, and machine learning, to improve the efficiency and quality of green technology innovation. Second, for enterprises in fourth- and fifth-tier cities, faced with the negative impact of DE on green technology innovation, they should consider adjusting their business strategies and exploring the possibility of cooperating with local governments, scientific research institutions, etc., to jointly develop green technology solutions suitable for the local environment. Finally, enterprises in resource-based cities face even greater challenges. Such enterprises should realize that relying on traditional resources alone is not enough to ensure long-term competitiveness. Therefore, they should seek to cooperate with enterprises in non-resource cities or introduce external digital technology solutions to promote green technology innovation in their enterprises. Taken together, these recommendations suggest that enterprises should continue to innovate in the era of DE and deeply explore the potential of digital technologies in promoting green technological innovation, while at the same time cooperating with all parties to address the challenges and ensure that they make great strides on the path to sustainable development.

7.3. Insufficient research

Although this study explores the association between DE, DR and GTI in depth, there are still some theoretical limitations. First, in explaining the relationship between DE and green technological innovation, this study mainly focuses on DR as a mediating mechanism, but this may have overlooked other potential mediating or moderating variables. In the broader literature in economics, DE may affect technological innovation through a variety of pathways, such as capital mobility, human capital accumulation, or intellectual property rights (IPR) regimes. And whether DR still plays a central role in these areas deserves further exploration. Second, although this paper emphasizes the threshold effect of DR, whether there are other potential theoretical explanations for the theoretical basis and economic mechanism behind it, which requires further research. Finally, the definition and delimitation of DE is still an evolving area in economics. Whether this study has captured the full range of DE impacts or whether there are specific digital technologies that have more significant impacts on green technological innovation are directions that can be further deepened in future research. In summary, this study has made a valuable contribution to the intersection of DE, DR and GTI, but there are still some theoretical shortcomings, which are expected to be explored more comprehensively and deeply in future research.

Author contributions

Conceptualization, YH and XZ; methodology, YH; software, YH; validation, YH and XZ; formal analysis, YH; investigation, YH; resources, YH; data curation, YH; writing—original draft preparation, YH; writing—review and editing, YH; visualization, YH; supervision, YH; project administration, YH; funding acquisition, XZ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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