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Enterprise Digital Transformation and Regional Green Innovation Efficiency Based on the Perspective of Digital Capability: Evidence from China

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Abstract: Under the dual pressure of economic development and environmental protection, it is urgent that we improve the efficiency of green innovation. Enterprise digital transformation brings opportunities to improve the efficiency of green innovation. However, most current studies focus on the relationship between the two from the micro level, ignoring the impact of enterprise digital transformation on the green innovation of other innovation entities within the region, and have not yet described it in detail from the perspective of digital capabilities. Therefore, based on Chinese data, this paper studies the impact of enterprise digital transformation on regional green innovation efficiency from the perspective of digital capability, and provides a theoretical reference for improving regional green innovation efficiency. The research shows that (1) the digital capabilities of enterprise digital transformation include digital acquisition capability, digital utilization capability, and digital sharing capability, which have significant promoting effects on regional green innovation efficiency; (2) strengthening information resources, knowledge resources, R&D funds, and human resources are the role channels indicated by mechanism analysis; (3) heterogeneity analysis shows that the promotion effect is not related to geographical location, but the disadvantaged areas of enterprise digital transformation and regional green innovation efficiency have a greater impact. Further, the applicability of the research conclusions is extended through case studies in other countries. This study enriches the research perspective of the relationship between enterprise digital transformation and green innovation, and provides a new path for regional sustainable development.

Keywords: digital transformation; green innovation efficiency; digital capability; mechanism analysis; heterogeneity analysis

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1. Introduction

China's economy continues to improve, but the accompanying environmental pollution cannot be ignored [1]. In the latest global-scale assessment of the environmental performance index, China's ranking is not ideal. Although China's efforts to protect the environment cannot be denied, this result also shows that improving the ecological environment performance is still an urgent task for China at this stage. Sustainable development theory also believes that the cost of developing the economy must not be to abandon the environment [2]. As a special form of innovation, green innovation is a good solution to this problem, because this innovation model can take into account the economy and the environment [3]. However, there are many obstacles in green innovation, such as long cycle, high risk, and difficulty in realization, which lead to the low efficiency of regional green innovation (*ERGI*) [4]. Therefore, promoting the *ERGI* can effectively alleviate the contradiction between economic growth and environmental pollution, and promote the sustainable development of regional economy.

With the introduction of Industry 4.0, as a major participant in green innovation, digitization has become an important support and inevitable choice for its development [5].

The digital transformation of enterprises (*DTE*) has a strong digital capability, which makes it easier to integrate fragmented innovation resources and knowledge organizations [6]. Meanwhile, the threshold for green innovation access will be lowered, and the interaction and cooperation between enterprises and other innovation entities will be strengthened. The strong digital ability of enterprises is conducive to promoting enterprises to collect massive information resources related to green innovation, realizing data mining at a deeper level, discovering new market demand and green innovation opportunities, improving product quality and supply and demand, matching efficiency [7,8], realizing the transfer, sharing, integration, utilization, and recreation of green innovation resources among innovation entities, and then improving the *ERGI*.

There is no doubt that the *DTE* will affect the efficiency of green innovation, and scholars have proved this view from multiple perspectives. Xue et al. (2022) found that *DTE* can promote green innovation from the perspective of transformation degree [9]. Stroud et al. (2020) believed that combining the application of digital technology with management strategies is helpful for enterprises to achieve green innovation cooperation [10]. Based on digital leadership, Sarfraz et al. (2022) found that *DTE* is a powerful engine for green product innovation and sustainable innovation performance [11]. Zhao et al. (2023) pointed out that the *DTE* strategy can promote green process and product innovation [12]. Although there are abundant studies on *DTE* and green innovation at present, digital capability, as an important dimension of *DTE* [13–15], is still rarely used to describe the relationship between *DTE* and green innovation. Moreover, the existing research mostly focuses on how the *DTE* acts on the green innovation of the enterprise, and does not consider the influence of the *DTE* on other enterprises or other innovation entities in the region. Accordingly, this paper aims to explore the impact of *DTE* on *ERGI* from the perspective of digital capability, and clarify the mechanism channels and regional heterogeneity of this effect, so as to enrich the theoretical research on *DTE* and *ERGI*.

This paper achieves these contributions: (1) Considering that the *DTE* will also affect the green innovation of other innovation entities in the region, and exploring the relationship between *DTE* and *ERGI* based on the perspective of digital capability, the *DTE* is divided into three dimensions: enterprise digital acquisition capability, digital utilization capability, and digital sharing capability, which expand the research perspective of the relationship between *DTE* and *ERGI*. (2) Based on the perspective of innovation resources, information resources, knowledge resources, R&D funds, and human resources are used as mediating variables to clarify the influence path of *DTE* and *ERGI*. (3) The heterogeneity analysis of the impact of *DTE* on *ERGI* considers geographical location and clustering results.

Other parts of the arrangement: Section 2 combs the research hypothesis and builds the theory. Section 3 expounds the research method. Section 4 provides results and discussion. Section 5 summarizes the conclusions.

2. Theoretical Analysis and Research Hypothesis

2.1. Baseline Hypothesis

The digital empowerment theory points out that in the process of *DTE*, based on information and communication technology, data elements and digital technologies are used to endow behaviors such as innovation resource allocation with digital characteristics, connectivity, intelligence, and analysis capabilities, and strengthen the collection, mining, and sharing capabilities of enterprise innovation resources [16,17]. According to the theory of green innovation, there are some problems in its implementation, such as high risk and long profit period, and then it faces the problems of insufficient innovation will of the innovation subject and difficulty in cooperation [18]. The realization of *DTE* can strengthen the digital capability [19], which is conducive to the analysis and utilization of green innovation resources of enterprises or the sharing with other innovation entities, thus accelerating the improvement of *ERGI*. Specifically, as an important factor of production in the digital era, data contain a lot of important information, which has an important impact on whether enterprises can grasp the green market dynamics, understand competitors, meet consumer needs, and, thus, gain opportunities. This also places a great test on the digital acquisition of enterprises. The strong digital acquisition capability of enterprises is not only conducive to obtaining more information [20], but also has a positive effect on the docking of various links of regional green innovation [21]. However, it is worth noting that, compared with traditional innovation, green innovation has greater risks and serious asymmetry of information resources. In the context of rapid digital development and enterprise digital transformation, although the digital information acquisition ability of enterprises has been strengthened, massive data resources make it difficult for enterprises to distinguish between true and false in the process of use. Therefore, enterprises should have the ability to effectively analyze and use a large number of data resources, screen valuable information in the data resources [22], promote enterprises to make breakthroughs in green innovation, help eliminate the concerns of enterprises when exchanging information with other innovation entities, and promote all kinds of innovation entities to jointly improve the *ERGI*. In addition, the *DTE* also facilitates the sharing of resources. In the process of *DTE*, enterprises use digital information technology to improve their own digital sharing ability, realize the intelligent matching between the supply side and the demand side, and then promote the exchange of information among regional innovation subjects. The complexity of the implementation process of green innovation determines the importance of green innovation cooperation, and enterprise digital sharing ability provides opportunities and convenience for green innovation cooperation [23–25]. Based on this, we believe that digital capability is a key dimension for *DTE* to promote the improvement of *ERGI*. Enterprise digital ability is considered to involve the use of modern digital technology to optimize processes, improve customer experience, and provide a new business model, with the ability to solve business problems [26,27], including digital acquisition, utilization, and sharing capability.

Enterprise digital acquisition capability is the ability to acquire digital resources. As the core subject of regional green innovation system, enterprises are the main organizers and participants of scientific and technological innovation activities [28]. Enterprises have high data collection capabilities, which are conducive to enriching the knowledge base of green innovation and strengthening the communication between enterprises and enterprises and other innovation entities, and have a positive impact on the *ERGI*. First, enterprises have higher digital acquisition capabilities, which is conducive to obtaining more information needed for business operations [20], increasing opportunities for cooperation and communication, and providing support for enterprises to obtain more new technologies and information. Second, enterprises should improve their digital acquisition capability, expand the method of collecting green innovation knowledge, enrich the knowledge base of regional green innovation [29], and provide more intellectual support for *ERGI*. Third, the content of green innovation is diverse, including multiple links. By enhancing digital collection capabilities, companies can efficiently deploy innovation resources to provide connectivity across manufacturing processes [21], thereby increasing *ERGI*. Moreover, the collected massive multidimensional high-frequency data also create conditions for the subsequent correlation analysis and in-depth mining of enterprises, thus forming an innovation model in terms of industrial resource organization, knowledge inheritance and diffusion, and providing a foundation for improving the *ERGI*.

Enterprise digital utilization capability refers to the ability of enterprises to analyze and sort out the acquired digital resources, remove redundant resources, screen data resources, and develop and utilize them. Strengthening the digital utilization capability of enterprises is conducive to mining valuable information from massive data, effectively coping with unpredictable changing environments [22], and improving the use of digital information and *ERGI*. In the digital era, enterprises are faced with massive data, but there are redundant and repetitive data resources, which is a double-edged sword for the improvement of *ERGI*. Compared with traditional innovation, green innovation faces higher costs, and this dilemma will be further amplified if the high-quality resources of green innovation cannot be efficiently identified. Strengthening enterprise digital analysis and utilization capabilities is conducive to integrating internal resources, forming key shared knowledge, identifying high-quality resources from massive data, improving resource exchange frequency, reducing costs [6], and, thus, improving *ERGI*. In the meantime, the improvement of enterprise digital utilization capability is conducive to enterprises' greater data mining space, deeper mining and use of data information, alleviating information asymmetry, rational use of resources [14], and promoting the exchange of innovative ideas between enterprises and other innovation subjects, so as to improve the *ERGI*.

Enterprise digital sharing capability is regarded as the ability of enterprises to share data resources with each other. Digital sharing ability affects the value co-creation between enterprises and other innovation entities. Improving enterprise digital sharing capability is conducive to promoting regional information sharing, strengthening the efficiency of innovation resource transfer and exchange, and it has a positive impact on *ERGI*. First, strengthening digital sharing capabilities can promote the transmission and exchange of resources and environment-related information within enterprises, improve the efficiency of green innovation information transmission and knowledge accumulation, expand the research and development path of green products, reduce research and development and operating costs, and encourage enterprises to participate in green innovation activities [30]. Second, the complexity of green innovation makes cooperation more important. Enterprises improve their digital sharing capabilities, which is conducive to information sharing [23], enhancing the familiarity of the green innovation collaboration process, and increasing the possibility of successful cooperation in regional green innovation. Third, digital sharing is conducive to enterprises obtaining external resources, accelerating the acquisition and absorption of heterogeneous knowledge, improving the accuracy of knowledge [24,25], promoting the flow of green innovation knowledge and new technologies, expanding the spillover effect of green innovation knowledge, and improving the *ERGI*.

In addition, the theory of green innovation holds that the study of green innovation should also take into account the actual situation of regional development [31]. From the perspective of regional development and civilization level, when the regional civilization level is improved, the regional green development awareness may be enhanced, which is more conducive to the improvement of the *ERGI* by enterprise digital capability. Urbanization rate refers to the proportion of urban population in the total population, which is often used to measure the level of regional economic development and civilization [32], and is also one of the important factors affecting green innovation. However, it is worth noting that although the improvement of regional civilization level is conducive to deepening the awareness of regional green development, with the increase of regional urbanization rate, a large number of residents flock to cities, which may lead to environmental pollution and emission increase, thus slowing down the improvement of *ERGI*. To sum up, although the specific impact of urbanization rate on *ERGI* cannot be determined, this factor still needs to be considered under the theme of this study. Similarly, the level of economic development cannot be ignored when studying the impact of enterprise digital capability on *ERGI* [33]. Regional economic development often determines the local innovation environment and the level of innovation infrastructure construction. This is also one of the factors that must be considered when exploring the relationship between an enterprise digital capability and the *ERGI* on a regional scale. From the perspective of regional industrial structure, optimizing industrial structure can improve the independent innovation ability of enterprises [34]. As a special form of innovation, green innovation is also affected by the industrial structure. It can be seen that the industrial structure is also one of the factors to be considered in this study. From the perspective of regional residents' quality of life, it mainly includes residents' consumption level and unemployment rate. When the consumption level of residents increases, to a certain extent, it means that residents' requirements for quality of life are improved, regional green environmental awareness is enhanced, green product purchase behavior is generated [35,36], and enterprises are forced to strengthen the role of digital capability in *ERGI*. Unemployment represents social sustainability [37]. When the unemployment rate rises, it will not only reduce the desire of consumers to buy green products, but will also lead to the low willingness of enterprises to invest in green products. At the same time, the local strategic planning will also change, and with a higher unemployment rate, the local government may face pressure to urgently solve the employment problem, and then promote the development of some high-energy industries, which is not conducive to the digital ability of enterprises to promote the *ERGI*. Therefore, in this study, the consumption level and unemployment rate of residents should also be included.

Based on the above analysis and considering the regional urbanization rate, economic development level, industrial structure, consumer consumption level, and unemployment rate, the following hypothesis is proposed:

In summary, the hypotheses are as follows:

H1: *DTE can positively affect ERGI.*

H1a: *Enterprise digital acquisition capability can positively affect ERGI.*

H1b: *Enterprise digital utilization capability can positively affect ERGI.*

H1c: *Enterprise digital sharing capability can positively affect ERGI.*

2.2. Mediating Effect Hypothesis

The improvement of enterprise digital capabilities means that enterprises rely on information technology such as big data to achieve cross-regional and cross-sectoral multi-integration. Digital technologies such as algorithms (digital twins, etc.), computing power (core chips, etc.), or data (Internet of Things and data perception) enable manufacturing, marketing, organizational models, product services, etc. By improving digital acquisition capabilities, the total amount of enterprise information resources is increased [29], which provides a basis for rational planning of green innovation and allocation of innovative resources. The improvement of enterprise digital utilization capability is conducive to enterprises' better use of artificial intelligence, blockchain analysis and big data technology, deeper mining of the hidden laws in massive data, improving the availability of information resources, and then helping enterprises to make the best production and sales decisions under the premise of complying with environmental laws, minimizing the negative impact on the environment and improving the *ERGI*. By improving the digital sharing ability, enterprises can fully realize the sharing of information resources, expand the regional resource sharing pool, accelerate the dissemination, transformation, absorption, and utilization of information resources, connect enterprises with partners [38], and improve the quality of access to green innovation information resources. To sum up, we point out the following hypotheses:

H2: *DTE indirectly improves ERGI by increasing information resources.*

H2a: *Enterprise digital acquisition capability indirectly improves ERGI by increasing information resources.*

H2b: *Enterprises digital utilization capability indirectly improves ERGI by increasing information resources.*

H2c: *Enterprise digital sharing capability indirectly improves ERGI by increasing information resources.*

Knowledge resources represent the amount of knowledge owned by enterprises. The improvement of digital acquisition capability of enterprises is conducive to improving the efficiency of data information collection by enterprises for users, collaborators, competitors in the same industry, etc. [39], timely understanding of market frontier information, enriching their own green innovation knowledge database, and helping to clarify their own development pain points, combined with their own situation, and formulate targeted measures to improve the level of knowledge resources. Enterprise digital utilization capability enhancement promotes the development of resources and knowledge integration. By analyzing the available knowledge information contained in massive data, it is helpful to understand the internal knowledge, quickly identify and integrate external knowledge, clearly grasp the mainstream technology, new ideas, and development trends of green innovation [40], and provide comprehensive and diversified knowledge resources for regional green innovation development. Enterprise digital sharing capabilities are enhanced to facilitate the sharing of heterogeneous knowledge resources with other green innovation participants. Thus, regions can obtain different and scarce green innovation knowledge resources, accelerate the conversion of tacit knowledge into usable knowledge resources, improve the knowledge spillover effect [24], and strengthen *ERGI*. On this basis, we propose the following hypotheses:

H3: *DTE indirectly improves ERGI by increasing knowledge resources.*

H3a: *Enterprise digital acquisition capability indirectly improves ERGI by increasing knowledge resources.*

H3b: *Enterprise digital utilization capability indirectly improves ERGI by increasing knowledge resources.*

H3c: *Enterprise digital sharing capability indirectly improves ERGI by increasing knowledge resources.*

Capital investment is the foundation of enterprise research and development. Green innovation, as a special form of innovation, has the characteristics of high investment, long return period, and high risk [41], and often lacks sufficient R&D funds. R&D funds investment is very critical to improving the *ERGI*. The strengthening of digital capabilities of enterprises is conducive to bringing more R&D funds to improve *ERGI* by identifying business opportunities and obtaining more investment funds. Specifically, the digital acquisition capability of enterprises can enhance the function of information collection, become the leader of digital innovation [13], discover the business opportunities of green products and services, achieve service value addition, improve user satisfaction, expand the scope of services, attract more investors to invest in regional green innovation, and provide financial guarantee for the development of regional green innovation. Through strong digital utilization capabilities, enterprises can realize data information mining and utilization, understand customer needs, make timely and accurate decisions [14,42,43], reduce operating costs, provide diversified production methods to promote enterprises to obtain new customers, increase value increment, and have more funds to invest in R&D links [44,45]. Similarly, enterprise digital sharing can also reduce transaction costs and marginal costs of services, improve the utilization rate of R&D funds [46], meet the changing market demand of consumers, expand market scale, enhance the value of innovation subjects, and use more funds for innovation R&D investment. Accordingly, the following hypotheses are proposed:

H4: *DTE indirectly improves ERGI by increasing R&D funds.*

H4a: *Enterprise digital acquisition capability indirectly improves ERGI by increasing R&D funds.*

H4b: *Enterprise digital utilization capability indirectly improves ERGI by increasing R&D funds.*

H4c: *Enterprise digital sharing capability indirectly improves ERGI by increasing R&D funds.*

Whether it is *DTE* or the improvement of *ERGI*, high-quality human capital is needed. Improving the quality of regional human capital is conducive to providing new ideas and new plans for regional green innovation [47,48], and thus enhancing *ERGI*. Specifically, the improvement of digital acquisition capability enables enterprises to understand the regional talent market more comprehensively, realize electronic human resource management [49], and realize the allocation efficiency of human resources more scientifically and reasonably. The improvement of digital utilization capability reduces the cost of human resources and information search, provides a platform for the exchange of talent information, ideas, and views within the innovation subject, stimulates the potential of talent, and improves the quality and ability of the original talent. The enhancement of enterprise digital sharing capability promotes the construction of regional talent information-sharing networks. Enterprises can not only share talent training plans and platforms, but also realize digital management of business process through data information resource sharing, clarifying the talent input demand of each link, and absorbing high-level talents [47]. Therefore, the following hypotheses are proposed:

H5: *DTE indirectly improves ERGI by improving human resources.*

H5a: *Enterprise digital acquisition capability indirectly improves ERGI by improving human resources.*

H5b: *Enterprise digital utilization capability indirectly improves ERGI by improving human resources.*

H5c: *Enterprise digital sharing capability indirectly improves ERGI by improving human resources.*

To sum up, a theoretical model of the impact mechanism of *DTE* on *ERGI* is proposed, as shown in Figure 1.

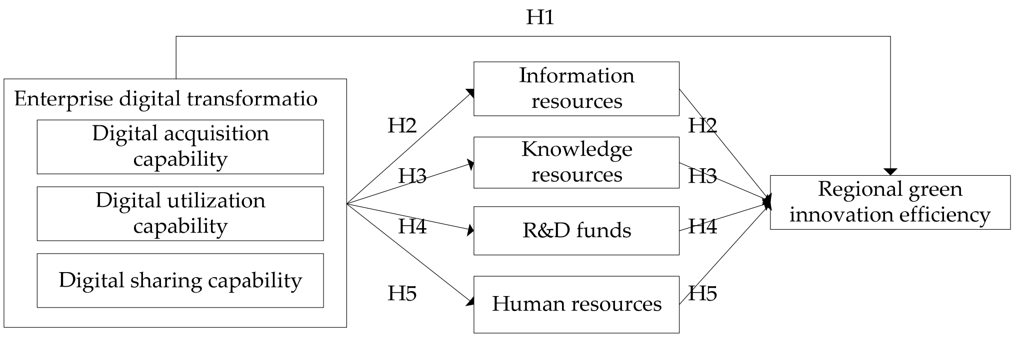

Figure 1. Theoretical model.

3. Research Methods

3.1. Variables

3.1.1. Explained Variables

Regional green innovation efficiency (*ERGI*): Patent data are often used to measure innovation efficiency due to their versatility and consistency [50]. In addition, patent licensing requires a certain fee and has a long time lag. Therefore, we take the total number of green patent applications in each provincial administrative region as a proxy variable for *ERGI*. From the type point of view, it is also divided into invention type and utility model patents; the former is more innovative than the latter. Accordingly, this paper takes the number of green invention patent applications (*RPI*) as a substitution variable for *ERGI* in the robustness test. In order to eliminate the dimensional differences between the data, the data are maximized.

3.1.2. Explanatory Variables

Enterprise digital transformation (*DTE*): Based on the perspective of digital capability, this paper mainly includes enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), and digital sharing capability (*ds*). At present, few studies strictly distinguish the measurement of different digital capabilities of enterprises. For listed companies, the annual report is an important report on the development strategy and ability of enterprises. Accordingly, we selected the Python crawler function to collect the annual reports of all A-share listed enterprises (Shanghai Stock Exchange and Shenzhen Stock Exchange), and divided the annual reports of enterprises by the dictionary of Python open source "Jieba". Referring to the *DTE* lexicon constructed by Zhao et al. (2021) [51] and Wu et al. (2021) [52], the frequency of related words was counted. On this basis, China National Knowledge Network, SCI, EI, core journals, CSSCI, and CSCD were used as the journal sources, and the relevant literature was retrieved with the keywords of "digital acquisition", "data acquisition", "data collection", "digital utilization", "data utilization", "digital sharing", and "data sharing". After manually eliminating redundant papers, meeting notices, and papers that did not fit the research topic, 79 papers with digital acquisition capability, 217 papers with digital utilization capability, and 364 papers with digital sharing capability were obtained. Word frequency analysis technology was used in combination with the meaning of words related to *DTE* to clarify the keywords of digital capability and calculate the frequency of their keywords, respectively (Table 1). In addition, the listed enterprises were matched according to the listing place and province, and the relevant word frequency of each provincial administrative region was finally taken as the proxy variable of *DTE*. In order to eliminate the dimensionless data, the word frequency was maximized.

Table 1. Keyword selection.

Variable	Keyword
Enterprise digital acquisition capability	stream computing, artificial intelligence, data mining, big data, multiparty security computing, augmented reality, Internet of Things, 100 million level concurrency, distributed computing, EB level storage, information software, information system, information network, memory computing, virtual reality, information terminal, information center, information integration, informatization, networking, industrial information, mixed reality, industrial communication, information physical system, heterogeneous data, cloud IT, cloud ecology, etc.
Enterprise digital utilization capability	image understanding, intelligent data analysis, Internet technology, investment decision aid system, natural language processing, intelligent environmental protection, text mining, semantic search, brain-like computing, green computing, cognitive computing, biometrics, intelligent transportation, face recognition, speech recognition, digital finance, data visualization, deep learning, information management, machine learning, Industrial Internet, credit investigation, mobile Internet, data management, digital control, data science, intelligent production, numerical control, intelligent wear, intelligent agriculture, intelligent medical care, etc.
Enterprise digital sharing capability	business intelligence, cloud computing, Internet action, Internet marketing, Internet model, B2B, B2C, C2B, C2C, O2O, Internet mobile, blockchain, digital currency, data platform, Internet strategy, data center, Internet application, e-commerce, information sharing, Internet healthcare, mobile payment, third-party payment, Internet thinking, NFC payment, intelligent robot, mobile Internet, e-commerce, Network connection, intelligent network connection, etc.

3.1.3. Mediating Variables

Mediating variables included information resources (*apt*), knowledge resources (*know*), R&D funds (*rdi*), and human resources (*hc*). Information resources (*apt*): Based on the number of websites owned by enterprises (number), Internet broadband access users (10,000 households), and the proportion of post and telecommunications business (CNY 100 million) in regional gross domestic product (GDP), the entropy method was used to calculate the comprehensive index. Knowledge resources (*know*) was measured by the entropy method of education funds (CNY 10,000), the number of undergraduate and junior college students (people) in general higher education, and the average years of education (years) of employed persons. R&D funds (*rdi*): Internal expenditure on R&D as a percentage of GDP. Human resources (*hc*): The total number of R&D personnel with doctorate degree, master's degree, and bachelor's degree was winsorized by 1%, respectively, and the data were maximized.

3.1.4. Control Variables

Based on the above theoretical analysis, it was also necessary to consider the urbanization rate, economic development level, industrial structure, consumer consumption level, and unemployment rate in the study of *DTE* and *ERGI* from the perspective of digital capability [32–37]. At the same time, this further ensured the rationality of the research results and overcame the influence of missing variables as much as possible. Regional urbanization rate (*ru*) is expressed as the proportion of urban population to the total resident population at the end of the year. The level of economic development (*gdp*) is expressed as GDP per capita. The industrial structure (*is*) is expressed as the proportion of the gross secondary industry to the gross domestic product (GDP) of the region. Consumer consumption level (*hgh*) is expressed as the proportion of total retail sales of social consumer goods (CNY 100 million) to regional gross domestic product (GDP). The unemployment rate (*r*) is expressed as the registered urban unemployment rate.

3.2. Model

3.2.1. Fixed Effect Model

The Hausman test was carried out on the relevant data of the relationship between enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), digital sharing capability (*ds*), and regional green innovation efficiency (*ERGI*). The result strongly rejects the null hypothesis, so a fixed effect model should be used to test the benchmark relationship. Fixed effects model can control some unobservable factors and alleviate endogenous problems. Based on this, a fixed effect model including time and individual was constructed with reference to the study of Lee et al. (2010) [53]. The model is as follows:

$$ERGI_{p,q} = \alpha + \beta DTE_{p,q} + \gamma Controls_{p,q} + \lambda_p + \mu_q + \varepsilon_{p,q} \quad (1)$$

Among them, *ERGI* is regional green innovation efficiency, *DTE* is enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), and digital sharing capability (*ds*), p and q represent provinces and years, respectively, *Controls* represents all control variables, λ_p represents individual fixed effect, μ_q represents time fixed effect, and $\varepsilon_{p,q}$ is a random disturbance term.

3.2.2. Mediating Effect Model

The causal step-by-step regression method proposed by Baron et al. (1986) is widely used in the action channel test [54], which can not only test the mediating role of a single variable, but also provide intuitive results [55–57]. Accordingly, the mediating effect model was constructed:

$$ERGI_{p,q} = \alpha^1 + \beta^1 DTE_{p,q} + \gamma^1 Controls_{p,q} + \lambda_p + \mu_q + \varepsilon_{p,q} \quad (2)$$

$$Mediator_{p,q} = \alpha^2 + \beta^2 DTE_{p,q} + \gamma^2 Controls_{p,q} + \lambda_p + \mu_q + \varepsilon_{p,q} \quad (3)$$

$$ERGI_{p,q} = \alpha^3 + \beta^3 DTE_{p,q} + \beta^{3'} Mediator_{p,q} + \gamma^3 Controls_{p,q} + \lambda_p + \mu_q + \varepsilon_{p,q} \quad (4)$$

Among them, *Mediator* is information resources (*apt*), knowledge resources (*know*), R&D funds (*rdi*), and human resources (*hc*).

In summary, the conceptual model diagram of this paper was drawn to help clarify the subsequent empirical analysis results of this paper, as shown in Figure 2.

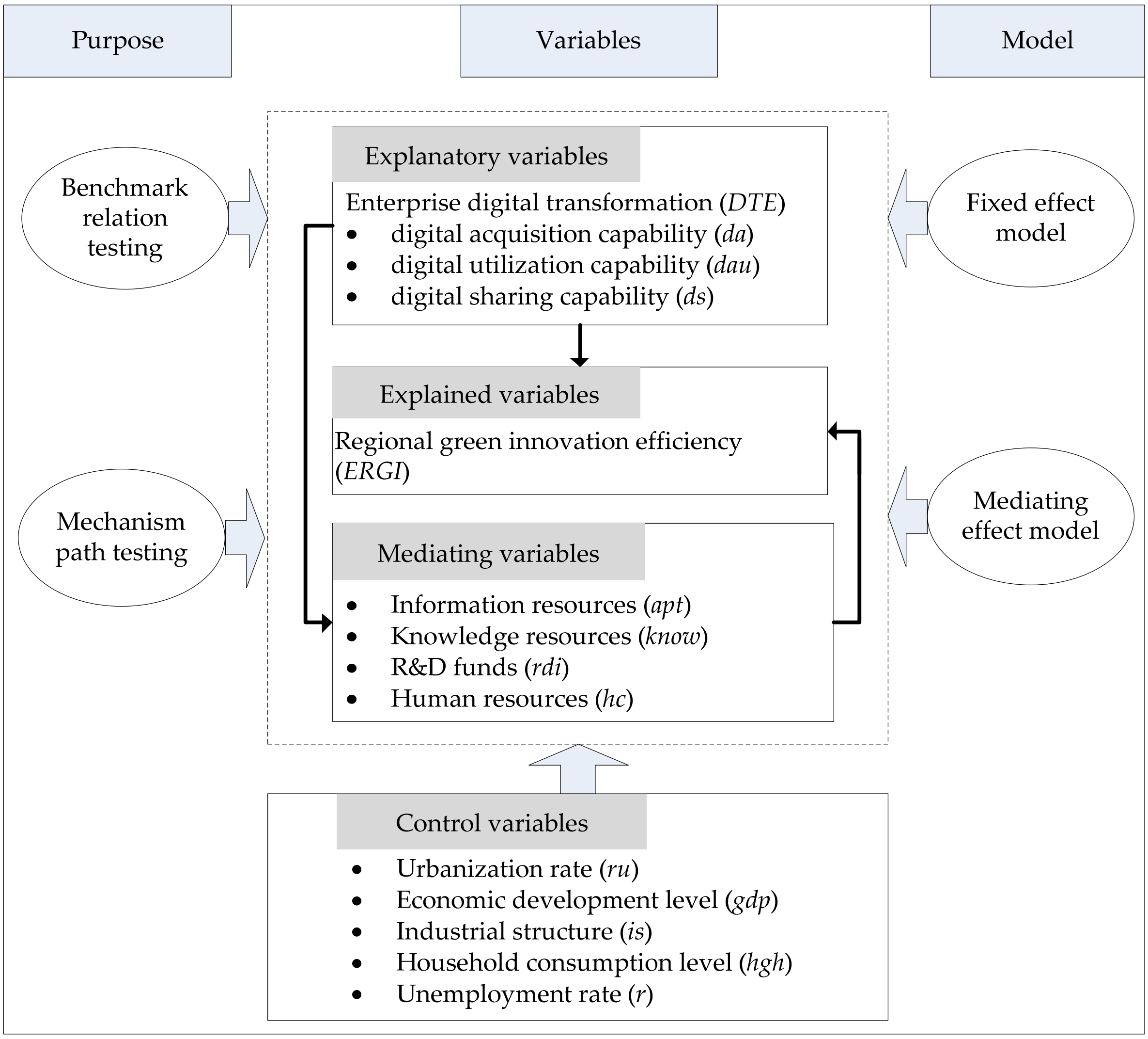

Figure 2. Conceptual model.

3.3. Research Samples and Data Sources

There are 34 provincial-level administrative regions in China, and there is a big gap in the development of politics, economy, culture, and education level among provincial-level administrative regions. Based on the provincial-level data, this paper explores the impact of *DTE* on *ERGI*. The coverage is more comprehensive, which is conducive to the realization of regional green coordinated development in provincial-level administrative regions, and is of great significance to improve the *ERGI*. In addition, the time series of provincial-level data is longer than that of urban-level data, and the missing values are fewer. Accordingly, this paper takes China's 30 provincial-level administrative regions (due to lack of data, Hong Kong, Macau, Taiwan, and Tibet are not included) as the research object, and the research interval was selected for 2013–2020.

Sources of measurement data involved variables. The China Research Data Service Platform (CNRDS) obtained green patent data to measure the explained variable "*ERGI*". The annual report data collected by Python web crawler came from the official websites of Shenzhen Stock Exchange and Shanghai Stock Exchange, and the data have been made public. The deadline for obtaining the data in this paper was 10 January 2023. The obtained data were used to measure the explanatory variables "enterprise digital acquisition capability", "enterprise digital utilization capability", and "enterprise digital sharing capability". The mediating variable of R&D funds and mediating variable of human resources were obtained from China Science and Technology Statistical Yearbook. The urban registered unemployment rate was derived from the China Population and Employment Statistical Yearbook, which is used to measure the unemployment rate of the control variable. The average years of education of employed people are derived from China Labor Statistics Yearbook, which is used as an indicator to measure knowledge resources. All indicators of information resources, residual indicators of knowledge resources (education funds, the number of undergraduate and junior college students (people) in general higher education), and the measurement data of control variables such as urbanization rate, economic development level, industrial structure, and residents' consumption level were derived from the China Statistical Yearbook.

4. Results

4.1. Descriptive Statistics

Descriptive statistics of the main variables in this chapter were performed using Stata15.0 64-bit software (Table 2). Results show that the maximum and minimum values of *ERGI* are quite different, indicating that there is a non-negligible gap in *ERGI*. Digital acquisition capability (*da*), digital utilization capability (*dau*), and digital sharing capability (*ds*) of enterprises not only have the same situation, but their mean and median are far lower than half of their maximum value, indicating that the current digital capability of enterprises in most areas of China is still in the initial stage of development, and the problem of unbalanced development is serious. Hence, based on digital capability, it is of practical significance to analyze the improvement path of *DTE* to *ERGI*.

Table 2. Descriptive statistics.

Variable	Mean	Median	SD	Maximum	Minimum	N
ERGI	0.139	0.0712	0.177	1.000	0.00152	240
da	0.0972	0.0363	0.165	1.000	0.00167	240
dau	0.0791	0.0263	0.137	1.000	0.000608	240
ds	0.103	0.0372	0.168	1.000	0.000978	240
apt	0.221	0.182	0.156	0.865	0.022	240
know	0.371	0.311	0.218	1.000	0.020	240
rdi	0.0172	0.0146	0.0114	0.0644	0.00446	240
hc	0.347	0.255	0.269	1.000	0.0238	240
ru	60.305	58.745	11.573	89.600	37.890	240
gdp	0.0810	0.0654	0.0695	1.000	0.0298	240
is	0.416	0.430	0.0832	0.573	0.158	240
hgh	0.393	0.400	0.0680	0.603	0.222	240
r	0.248	0.214	0.108	0.560	0.0950	240

4.2. Benchmark Regression Analysis

Regression results of enterprise digital transformation and regional green innovation efficiency are shown in Table 3. Columns (1)–(2) show the regression results of enterprise digital acquisition capability (*da*) and *ERGI*. Column (1) only considers the fixed effect of province and time, and further adds control variables to column (2). Both regression coefficients are significantly positive. Columns (3)–(4) show the regression of digital utilization capability (*dau*) and *ERGI*, which also passes the significance test. Columns (5)–(6) show the regression between digital sharing capability (*ds*) and *ERGI*, and the correlation coefficient is also significantly positive. Summary analysis, Hypothesis 1 is verified.

Table 3. Benchmark regression.

	ERGI(1)	*ERGI(2)*	*ERGI(3)*	*ERGI(4)*	*ERGI(5)*	*ERGI(6)*
da	0.640 ***	0.721 ***				
	(0.0887)	(0.0860)				
dau			1.002 ***	1.075 ***		
			(0.123)	(0.137)		
ds					0.796 ***	0.931 ***
					(0.106)	(0.104)
ru		0.00871 ***		0.00666 ***		0.00963 ***
		(0.00282)		(0.00228)		(0.00281)
gdp		−0.146		0.0357		−0.268
		(0.407)		(0.413)		(0.385)
is		−0.0747		−0.119		−0.145
		(0.125)		(0.119)		(0.118)
hgh		−0.0218		−0.0158		−0.00791
		(0.0572)		(0.0597)		(0.0593)
r		0.0854		0.120 *		0.146 **
		(0.0666)		(0.0658)		(0.0691)
_cons	0.0767 ***	−0.427 ***	0.0608 ***	−0.323 ***	0.0572 ***	−0.489 ***
	(0.00877)	(0.153)	(0.00913)	(0.123)	(0.0107)	(0.155)
year	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240	240
R^2	0.948	0.953	0.956	0.959	0.950	0.956

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Endogenous Treatment and Robustness Test

There may be a reverse causal problem between the explanatory variables and the explained variables; therefore, the instrumental variable method was used to alleviate the impact of this endogenous problem and conduct an endogenous test. The explanatory variables included enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), and digital sharing capability (*ds*). There are relatively few existing studies, and most of them integrate enterprise digital transformation into an indicator to measure it. Based on this situation, this paper refers to the research idea of Zhao et al. (2023) [58], and lags the core explanatory variables as instrumental variables (*iv_da*, *iv_dau*, *iv_ds*). The explanatory variables of the lag phase are related to the current core explanatory variables, but not related to the disturbance term, which meets the correlation and exogenous requirements of the instrumental variables. The results in Table 4 show that Hypothesis 1 still holds when considering endogenous problems.

Table 4. Endogenous treatment.

	da(1)	*ERGI(2)*	*dau(3)*	*ERGI(4)*	*ds(5)*	*ERGI(6)*
da		0.640 ***				
		(0.0861)				
iv_da	0.966 ***					
	(0.0564)					
dau				1.054 ***		
				(0.139)		
iv_ dau			0.971 ***			
			(0.0869)			
ds						1.058 ***
						(0.135)
iv_ds					0.847 ***	
					(0.0540)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. *Cont.*

	da(1)	*ERGI(2)*	*dau(3)*	*ERGI(4)*	*ds(5)*	*ERGI(6)*
_cons	0.230 ***	−0.674 ***	0.147 **	−0.573 ***	0.301 ***	−0.968 **
	(0.0751)	(0.251)	(0.0604)	(0.193)	(0.0642)	(0.250)
year	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes
N	210	210	210	210	210	210
R^2		0.962		0.964		0.960
First-stage F statistic	293.270 ***		124.820 ***		245.610 ***	
Cragg–Donald Wald F statistic	1725.372 [16.38]		1018.023 [16.38]		1456.726 [16.38]	
Kleibergen–Paap rk LM statistic	20.783 ***		19.329 ***		17.322 ***	

** $p < 0.05$, *** $p < 0.01$.

In addition, the robustness test was carried out by removing special samples and changing the measurement methods of variables. In Table 5, columns (1)–(3) are municipalities excluded, columns (4)–(6) are *ERGI* measured by the total number of green invention patent applications (*RPI*), and columns (7)–(9) have 2020 sample data excluded. The correlation coefficient obtained by the test is still significantly positive, and Hypothesis 1 is still valid.

Table 5. Robustness test.

	ERGI(1)	*ERGI(2)*	*ERGI(3)*	*RPI(4)*	*RPI(5)*	*RPI(6)*	*ERGI(7)*	*ERGI(8)*	*ERGI(9)*
da	0.842 ***			0.670 ***			0.792 ***		
	(0.0838)			(0.0671)			(0.0918)		
dau		1.144 ***			0.910 ***			1.279 ***	
		(0.142)			(0.110)			(0.112)	
ds			1.050 ***			0.832 ***			1.029 ***
			(0.113)			(0.0800)			(0.102)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.195	−0.150	−0.262 **	−0.236 **	−0.109	−0.275 **	−0.389 **	−0.304 **	−0.451 ***
	(0.137)	(0.109)	(0.129)	(0.119)	(0.117)	(0.124)	(0.161)	(0.127)	(0.159)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	208	208	208	240	240	240	210	210	210
R^2	0.966	0.967	0.967	0.950	0.947	0.949	0.955	0.965	0.959

** $p < 0.05$, *** $p < 0.01$.

4.4. Intermediary Mechanism Tests

Table 6 shows the test results of the mediating effect of information resources on DTE and *ERGI*. Among them, columns (1)–(3) show the mediating effect test of information resources (*apt*) between enterprise digital acquisition capability (*da*) and *ERGI*, columns (4)–(6) show the mediating effect test of information resources (*apt*) between enterprise digital utilization capability (*dau*) and *ERGI*, and columns (7)–(9) show the mediating effect test of information resources (*apt*) between enterprise digital sharing capability (*ds*) and *ERGI*. The results show that the intermediary effect of information resources (*apt*) on the relationship between *DTE* and *ERGI* is thorough; that is, Hypothesis 2 is established.

Table 7 shows the test results of the mediating effect of knowledge resources on *DTE* and *ERGI*. Among them, columns (1)–(3) show the mediating effect test of knowledge resources (*know*) between enterprise digital acquisition capability (*da*) and *ERGI*, columns (4)–(6) show the mediating effect test of knowledge resources (*know*) between enterprise digital utilization capability (*dau*) and *ERGI*, and columns (7)–(9) show the mediating effect test of knowledge resources (*know*) between enterprise digital sharing capability (*ds*) and *ERGI*. The results show that the intermediary effect of knowledge resources (*know*) on the relationship between *DTE* and *ERGI* is thorough; that is, Hypothesis 3 is established.

Table 6. Mediating role of information resources.

	ERGI(1)	apt(2)	ERGI(3)	ERGI(4)	apt(5)	ERGI(6)	ERGI(7)	apt(8)	ERGI(9)
da	0.721 ***	0.101 *	0.679 ***						
	(0.0860)	(0.0534)	(0.0797)						
dau				1.075 ***	0.134 *	1.019 ***			
				(0.137)	(0.0775)	(0.133)			
ds							0.931 ***	0.140 **	0.879 ***
							(0.104)	(0.0707)	(0.103)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
apt			0.415 ***			0.416 ***			0.367 ***
			(0.141)			(0.114)			(0.135)
_cons	−0.427 ***	−0.357 *	−0.278	−0.323 ***	−0.337 *	−0.183	−0.489 ***	−0.372 *	−0.353 **
	(0.153)	(0.195)	(0.180)	(0.123)	(0.186)	(0.145)	(0.155)	(0.201)	(0.174)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240	240	240	240	240
R^2	0.953	0.975	0.956	0.959	0.975	0.963	0.956	0.976	0.958

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Mediating role of knowledge resources.

	ERGI(1)	know(2)	ERGI(3)	ERGI(4)	know(5)	ERGI(6)	ERGI(7)	know(8)	ERGI(9)
da	0.721 ***	0.155 ***	0.617 ***						
	(0.0860)	(0.0525)	(0.0698)						
dau				1.075 ***	0.266 ***	0.937 ***			
				(0.137)	(0.0602)	(0.126)			
ds							0.931 ***	0.208 ***	0.802 ***
							(0.104)	(0.0658)	(0.0887)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
know			0.668 ***			0.518 ***			0.619 ***
			(0.109)			(0.0904)			(0.0941)
_cons	−0.427 ***	−0.0456	−0.396 ***	−0.323 ***	−0.0355	−0.305 **	−0.489 ***	−0.0634	−0.450 ***
	(0.153)	(0.115)	(0.142)	(0.123)	(0.120)	(0.118)	(0.155)	(0.117)	(0.143)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240	240	240	240	240
R^2	0.953	0.963	0.961	0.959	0.966	0.964	0.956	0.964	0.963

** $p < 0.05$, *** $p < 0.01$.

Table 8 shows the test results of the mediating effect of R&D funds on *DTE* and *ERGI*. Among them, columns (1)–(3) show the mediating effect test of R&D funds (*rdi*) between enterprise digital acquisition capability (*da*) and *ERGI*, passing the significance test. Columns (4)–(6) show the mediating effect test of R&D funds (*rdi*) between enterprise digital utilization capability (*dau*) and *ERGI*, passing the significance test. Columns (7)–(9) show the mediating effect test of R&D funds (*rdi*) between enterprise digital sharing capability (*ds*) and *ERGI*, passing the significance test. Therefore, Hypothesis 4 is true.

The test results of the mediating effect of human resources on *DTE* and *ERGI* are shown in Table 9. Columns (1)–(3), (4)–(6), and (7)–(9), respectively, show the mediating effect test of human resource (*hc*) in the relationship between enterprise digital acquisition capability (*da*), enterprise digital utilization capability (*dau*), enterprise digital sharing capability (*ds*), and *ERGI*. The correlation regression coefficients are all significantly positive; that is, Hypothesis 5 is true.

Table 8. Mediating role of R&D funds.

	ERGI(1)	*rdi(2)*	*ERGI(3)*	*ERGI(4)*	*rdi(5)*	*ERGI(6)*	*ERGI(7)*	*rdi(8)*	*ERGI(9)*
da	0.721 ***	0.00414 **	0.692 ***						
	(0.0860)	(0.00184)	(0.0806)						
dau				1.075 ***	0.00696 **	1.038 ***			
				(0.137)	(0.00309)	(0.136)			
ds							0.931 ***	0.00529 **	0.896 ***
							(0.104)	(0.00236)	(0.0987)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rdi			6.886 ***			5.242 **			6.613 ***
			(2.255)			(2.372)			(2.176)
_cons	−0.427 ***	0.00905 *	−0.489 ***	−0.323 ***	0.00937 **	−0.372 ***	−0.489 ***	0.00872 *	−0.547 ***
	(0.153)	(0.00477)	(0.144)	(0.123)	(0.00466)	(0.114)	(0.155)	(0.00478)	(0.145)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240	240	240	240	240
R^2	0.953	0.989	0.955	0.959	0.989	0.960	0.956	0.989	0.958

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Mediating role of human resources.

	ERGI(1)	*hc(2)*	*ERGI(3)*	*ERGI(4)*	*hc(5)*	*ERGI(6)*	*ERGI(7)*	*hc(8)*	*ERGI(9)*
da	0.721 ***	0.533 ***	0.651 ***						
	(0.0860)	(0.0758)	(0.0905)						
dau				1.075 ***	0.738 ***	0.994 ***			
				(0.137)	(0.108)	(0.148)			
ds							0.931 ***	0.644 ***	0.844 ***
							(0.104)	(0.0919)	(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
hc			0.131 **			0.109 *			0.135 **
			(0.0625)			(0.0555)			(0.0580)
_cons	−0.427 ***	−0.656 ***	−0.341 **	−0.323 ***	−0.560 **	−0.262 **	−0.489 ***	−0.677 ***	−0.398 **
	(0.153)	(0.245)	(0.161)	(0.123)	(0.229)	(0.133)	(0.155)	(0.244)	(0.163)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	240	240	240	240	240	240	240	240	240
R^2	0.953	0.970	0.954	0.959	0.970	0.960	0.956	0.969	0.957

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Regional Heterogeneity Analysis

Based on the three regions classified by the website of the National Bureau of Statistics (NBS), namely, the eastern, central, and western regions, the regional heterogeneity of the geographical location of the impact of *DTE* on *ERGI* was explored by grouping regression (Table 10). Columns (1)–(3) show the regression results of digital acquisition capability (*da*), digital utilization capability (*dau*), digital sharing capability (*ds*), and *ERGI* of the eastern region. Columns (4)–(6) represent the regression results of the central region, and columns (7)–(9) represent the regression results of the western region. All correlation regression coefficients are significantly positive, indicating that the impact of *DTE* on *ERGI* is not correlated with the region to which enterprises belong, and it also indicates that *DTE* has a strong positive effect on *ERGI*.

On this basis, the regional heterogeneity of *DTE* on *ERGI* is further discussed, using K-mean clustering analysis. The average values of enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), digital sharing capability (*ds*), and *ERGI* from 2013 to 2020 were calculated, and these four variables were used as the basis for clustering. The clustering number was set to 2, 3, and 4, respectively. Through comparative analysis of clustering results, it was found that the clustering number was more reasonable when it was 3. Among them, Category I includes Beijing and Guangdong, which represents the top regions for *DTE* and *ERGI*. Category II includes Shanghai, Jiangsu, Zhejiang, and Shandong, where the *DTE* and *ERGI* are also high, above the national average level, but there is a certain gap compared with Beijing and Guangdong. Category III includes the remaining provincial-level regions, mainly located in the central and western regions, where the *DTE* and *ERGI* is weak compared to Category I and Category II regions.

Table 10. Regional heterogeneity analysis of geographical location.

		Eastern			Central			Western	
	ERGI(1)	*ERGI(2)*	*ERGI(3)*	*ERGI(4)*	*ERGI(5)*	*ERGI(6)*	*ERGI(7)*	*ERGI(8)*	*ERGI(9)*
da	0.722 ***			1.430 ***			0.711 **		
	(0.0925)			(0.287)			(0.282)		
dau		1.091 ***			0.931 ***			1.045 **	
		(0.149)			(0.225)			(0.512)	
ds			0.932 ***			1.223 ***			1.310 ***
			(0.108)			(0.392)			(0.343)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.815 ***	−0.476 **	−0.725 **	−0.209 **	−0.239 ***	−0.286 ***	0.282 **	0.176	0.141
	(0.287)	(0.219)	(0.275)	(0.0876)	(0.0862)	(0.0909)	(0.140)	(0.148)	(0.150)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	88	88	88	64	64	64	88	88	88
R^2	0.953	0.963	0.956	0.952	0.940	0.939	0.918	0.904	0.920

** $p < 0.05$, *** $p < 0.01$.

Based on the results of K-means cluster analysis, the group regression explores the regional heterogeneity analysis of *DTE* on *ERGI* in depth (Table 11). Columns (1)–(3), (4)–(6), and (7)–(9) represent the regression results of enterprise digital acquisition capability (*da*), digital utilization capability (*dau*), digital sharing capability (ds), and *ERGI* in Class I, Class II, and Class III regions, respectively. It can be found that enterprise digital acquisition capability can significantly promote *ERGI*, in Category I and Category III regions, and enterprise digital utilization capability (*dau*) and digital sharing capability (*ds*) can significantly promote *ERGI* in Class III regions. It can be seen that for regions with weak efficiency of *DTE* and *ERGI*, enterprises should actively cultivate their digital acquisition capabilities, digital utilization capabilities, and digital sharing capabilities, so as to enhance *ERGI*.

Table 11. Regional heterogeneity analysis based on clustering.

		Category I			Category II			Category III	
	ERGI(1)	*ERGI(2)*	*ERGI(3)*	*ERGI(4)*	*ERGI(5)*	*ERGI(6)*	*ERGI(7)*	*ERGI(8)*	*ERGI(9)*
da	1.286 *			−0.297			0.806 ***		
	(0.133)			(0.338)			(0.164)		
dau		1.017			0.365			0.928 ***	
		(0.175)			(0.755)			(0.174)	
ds			1.021			−0.136			0.915 ***
			(0.198)			(0.573)			(0.171)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−11.33	0.240	3.303	−0.950	−1.053 *	−1.062	−0.0179	−0.00396	−0.0619
	(2.114)	(5.101)	(6.231)	(0.595)	(0.565)	(0.610)	(0.0689)	(0.0653)	(0.0738)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16	16	16	32	32	32	192	192	192
R^2	1.000	0.999	0.999	0.957	0.957	0.956	0.907	0.895	0.899

* $p < 0.1$, *** $p < 0.01$.

4.6. Case Studies of Other Countries

Case studies are of great benefit to further explore the usability of research conclusions from a practical point of view [59]. In the previous narrative, we used Chinese provincial data to empirically test the relationship between *DTE* and *ERGI* from the perspective of digital capabilities. Although this research is based on the actual situation in China, in the context of rapid digital development and increasing environmental pollution, other foreign countries are also facing the need to use digital transformation to improve the *ERGI*. Therefore, it is indispensable to analyze typical foreign cases and provide reference for other countries in the world.

Smart cities, as outstanding examples of digital transformation for sustainable economic and social development, have been promoted by governments and businesses around the world [60]. Although the digital transformation problem studied in this paper is based on the enterprise level, and a smart city is the digital transformation at the city level, enterprises, as an important stakeholder of smart city, play a non-negligible role in the urban digital transformation. At the same time, this also confirms the research idea of this paper. *DTE* is not only limited to influencing internal green innovation, but also has an impact on other innovation entities in the region. Because Singapore and the European Union (EU) are relatively successful representatives of smart city development on a global scale [60–62], the smart city construction in Singapore and the European Union is selected for the case study.

The construction of smart cities in Singapore began in the 1980s, and it is one of the earlier and more representative countries in the world. Singapore's smart city construction mainly includes two aspects: smart city infrastructure construction and digital economy ecosystem construction. After the formulation of the strategic plan for the construction of smart cities, the Singapore government has actively promoted the development of digital economy, built digital infrastructure and a digital industry ecosystem, provided opportunities for regional green innovation with urban digital transformation, and promoted the sustainable development of regional economy [60]. Although the smart city is promoted by the government, it is found in the process of Singapore's smart city construction that if you want to achieve sustainable development through smart cities, you need the joint efforts of the government, enterprises, and all parties in society. Only by cooperating with each other and jointly promoting regional digitalization and smart construction can we improve energy utilization efficiency, reduce energy waste, improve regional green and innovative development, and promote sustainable economic and social development.

In the context of the need to promote clean energy and sustainability, the EU sees smart cities as an important initiative to achieve this goal [62]. Similarly, when developing smart cities, the EU also pointed out that the use of smart city construction and the realization of digital transformation to promote sustainable development cannot be completed by one party, but requires multiple stakeholders, including enterprises, governments, universities, citizens, and so on [61]. Among them, Stockholm in Sweden and Amsterdam in the Netherlands are both successful areas in the construction of smart cities. They stressed the importance of digital transformation for regional sustainable development. Support from digital information technology is conducive to improving the collection and utilization of data information resources and realizing knowledge sharing.

To sum up, although this study takes the enterprise level as the research object of digital transformation, and the smart city is at the city level, the positive role of *DTE* on regional sustainable development is also emphasized in the smart city, which is consistent with our view to some extent. At the same time, in the construction of smart cities, Singapore and the EU have pointed out that they should not only rely on one side, but should combine the forces of enterprises, governments, universities, the public, and other parties to jointly achieve regional sustainable development through close cooperation, and they have also pointed out the important role of data information resources collection, utilization, and sharing. This paper confirms the rationality of exploring the relationship between *DTE* and *ERGI* based on the perspective of digital capability. In short, in the process of case analysis, it not only supports the above theoretical and empirical analysis results, but also expands the applicability of the research conclusions of this paper, proving that *ERGI* can be improved through *DTE* based on the perspective of digital capability not only in China, but also in other countries abroad. However, it is worth noting that it is necessary to formulate a strategic plan suitable for its own development according to its own actual situation. In addition, it also gives us inspiration for future research: digital transformation should not only focus on the enterprise level; the digital transformation of other stakeholders in the region is also important for sustainable development.

4.7. Discussion

Enterprises are the main force of scientific and technological innovation and the main body of regional green innovation. Under the trend of digitalization, promoting the *DTE* provides opportunities for improving the *ERGI*. Many studies have noted the positive impact of *DTE* on green innovation [9,63–65], but most studies only focus on the micro level. *DTE* not only affects the green innovation development of the enterprise, but also affects other innovation subjects in the region. However, there is still a lack of research on how the *DTE* affects green innovation at the regional level. In addition, studies on the impact of the relationship between *DTE* and green innovation are mostly conducted from the perspectives of digital transformation degree [9], digital technology application [10], digital leadership [11], and digital strategy [12], while there are few studies from the perspective of digital capability, which is one of the important dimensions of *DTE*. Based on this, we discuss the impact of *DTE* on *ERGI* from the perspective of digital capability. It can be said that it has enriched the theoretical research of *DTE* and green innovation.

The results show that from the perspective of digital capability and regional level, the impact of *DTE* on *ERGI* is still positive. At the same time, we find that the channel mechanism of this positive effect is achieved by improving innovation resources, including information resources, knowledge resources, R&D funds, and human resources. He et al. (2023) also pointed out that the *DTE* can strengthen the resources and knowledge base, and then have an impact on green innovation [65], which is similar to our conclusion. In addition, after noting the current digital divide problem [66–68], we further explored whether there is heterogeneity in the role of digital capabilities in promoting *ERGI* based on geographical location and clustering results. The study found that although this promotion effect is not related to geographical location, it is related to the digital capabilities of local enterprises and the *ERGI*. Where the digital capabilities of enterprises and *ERGI* are poor, it is more conducive to play this role, which just provides guidance for the coordinated development of *ERGI*. Therefore, for the weak areas of *ERGI*, it is necessary to increase the support for the *DTE* of local enterprises, so as to narrow the gap of *ERGI*. In addition, we further extended the applicability of the conclusions of this study through the case analysis of smart cities in Singapore and the EU. In the analysis process, we also found that the positive effect of digital transformation on regional sustainable development should not only be limited to the enterprise level; it is also important to other stakeholders in the region, including the government, universities, and the public.

5. Conclusions

5.1. Main Conclusions

Based on sustainable development theory, green innovation theory, and digital empowerment theory, this paper studies the impact of *DTE* on *ERGI* from the perspective of digital capability by using Chinese provincial level data. The main conclusions are as follows.

(1) The digital capabilities of *DTE* mainly include acquisition, utilization, and sharing, which have a significant role in promoting *ERGI*. This not only enriches the research perspective of the relationship between *DTE* and green innovation but also promotes the cross-integration of digital empowerment theory and green innovation theory.

(2) Enterprise digital acquisition capabilities, digital utilization capabilities, and digital sharing capabilities can improve *ERGI* by strengthening information resources, knowledge resources, R&D funds, and human resources. It not only expands the research content of sustainable development theory from the perspective of regional innovation and environmentally sustainable development, but also provides a new path for regional promotion of green innovation development.
(3) The positive impact of *DTE* on *ERGI* has little correlation with geographical location, but the regional heterogeneity analysis based on clustering shows that the positive impact is greater for regions where *DTE* and *ERGI* are weak. Based on the heterogeneity of regional development, the paper highlights the differences in the relationship between *DTE* and *ERGI* in different regions, which deepens the research on digital empowerment theory and green innovation theory, and also provides references for various regions to formulate regional green innovation development strategies according to local conditions.

It is worth noting that on the basis of empirical analysis of Chinese data, this paper further conducts case studies on smart cities in Singapore and the EU to expand the applicability and influence of this study. However, it must be remembered that when other countries and regions learn from the conclusions of this study, they should formulate appropriate strategic planning based on their own actual conditions.

5.2. Policy Recommendations

Based on the conclusions, the following suggestions are proposed for China to better play the role of *DTE* in promoting *ERGI* based on digital capabilities.

(1) Strengthening digital capabilities for enterprise digital transformation. Digital development strategies and construction targets should be formulated according to local conditions. Beijing, Guangdong, Shanghai, Jiangsu, Zhejiang, Shandong, and other regions with strong digital capabilities should increase continuous investment in the Internet industry and further strengthen infrastructure construction and supporting services. Additionally, other areas with insufficient digital capabilities of enterprises should play the role of market players, stimulate the innovation vitality of innovation players in all fields and at all levels, and strengthen the construction of digital platform. In the meantime, they should give play to the overall role of the government to promote the establishment of digital resources quality management system, and enhance the overall awareness of the digital resources related units in the region, popularize the legal protection and interest advantages of digital resources sharing, and give play to local advantages. They should summarize and promote the experience and practice of advanced regions such as Beijing, Guangdong, and Shanghai, improve the planning and design from top to bottom, promote the docking of government digital resources and social digital resources, and expand the benefits of digital sharing.

(2) Improving the optimal allocation of innovation resources. Local governments should play a good role in organizing and guiding. Upwards, the government should actively strive for the central support, relying on the national strategy of science and technology strength and key laboratories of building areas, to attract top talent at home and abroad, and to optimize the trans-regional optimized allocation of innovation resources and communities in promoting innovation resources flow between regions. Downward, the government should focus on the problems existing in the allocation of innovation resources of green innovative enterprises, including those above the scale and those at the top position. By establishing industrial alliances and innovation consortiums, advantageous resources can be integrated. Through the vertical integration of the industrial chain and the optimal combination of innovation resources, we will strengthen the advantages of technological innovation and the transformation of scientific research achievements upstream and downstream of the industrial chain, and seek a wider range of cooperation.

Similarly, these policies are based on China's actual situation, but they can also provide reference for other countries and regions. However, other countries and regions should adjust their strategic plans according to their actual conditions.

5.3. Limitations and Future Research

There are still shortcomings in the existing research:

(1) Research data are of the timespan of less than ten years. The data will be further updated and the timespan extended in the future to verify the accuracy and rationality of the research conclusions. In addition, the research data in this paper are limited to China, although we have also conducted case studies of other countries. Other countries should adjust their strategic planning according to their own conditions when referring to the conclusions of this study.
(2) The relationship between *DTE* and *ERGI* is only discussed from a static perspective, without considering a dynamic perspective, which will be the direction for further improvement of this study in the future. At the same time, with the in-depth development of digitalization, the relationship between *DTE* and *ERGI* from the perspective of space can be further discussed in the future.
(3) In the research process, although we consider the differences in the current economy, industrial structure, consumption, and employment of different regions, the natural ecological environment and the degree of ecological environment control in different regions may also have an impact on the research results regarding the relationship between *DTE* and *ERGI*. This is also one of the future improvement directions.

In view of the above shortcomings, future studies will expand the data time range and verify the conclusions of this paper with data from other countries. At the same time, from the dynamic and spatial perspectives, the relationship between *DTE* and *ERGI* is constantly deepened. Furthermore, the ecological environment and environmental control in each region are further included in the study.

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