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Digital Transformation and Green Development Research: Microscopic Evidence from China's Listed Construction Companies

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Abstract: The construction industry is in urgent need to transition away from its rough development and management practices. It is essential to embrace a sustainable development path to enhance core competitiveness, promote resource intensification, and prioritize environmental friendliness. The digital transformation uses information and data as the key elements to promote the transformation of traditional industries to become more intelligent and green. This ushers in new opportunities for transformation in the construction industry, marking a significant turning point for its evolution. This paper explores the impact of digital transformation on the green development of construction companies and its inner mechanism. Based on the panel data of the listed companies in China's construction industry from 2015 to 2021, the two-way fixed effect, mediating effect, moderating effect, and threshold effect models are used to test the relationship between them. The results indicate that digital transformation significantly promotes the green development of construction companies. Additionally, this result still holds after robustness and endogeneity tests. This effect is more significant in state-owned, larger companies situated in regions with weaker digital economy development. In addition, the intensity of regional environmental regulations strengthens the impact of digital transformation on green development. However, it has a threshold effect. In the test of mediating effect, it has been found that green innovation and corporate human capital structure can serve as mediators. In the general trend of digital change, the drive towards the sustainable development of construction companies offers micro-empirical evidence that the digital economy empowers green development in China.

Keywords: construction industry; digital transformation; green development; green technology; human capital structure; environmental regulation; threshold effect

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1. Introduction

The concept of "green development" has received widespread attention since it was introduced by the United Nations Development Programme (UNDP) in 2002. In recent years, with global warming, frequent extreme weather, and a series of environmental problems becoming more and more serious, environmental issues have gained significant attention from countries worldwide [1]. In the face of the severity of climate change, carbon neutrality has also become a common goal for both developed and developing countries [2]. To achieve energy conservation, emission reduction, and facilitate industrial transformation and upgrading, China is committed to reaching its peak CO_2 emissions before 2030 and achieving carbon neutrality before 2060. The construction of the "dual carbon" goal is a major strategy developed by China based on the requirements of its internal sustainable development, and its shared responsibility in creating a global community for the future. In the new era, it is a strategic need for China's sustainable development to shift away from the model of inefficient and blind development crude, and instead explore a more nuanced developmental approach focused on environmental protection and the high-quality advancement of economics [3]. The construction industry is a pillar industry in China. According to the data of the China Statistical Yearbook, the total output value of the national construction industry in 2022 was RMB 31,198 billion, accounting for 25.78% of the gross domestic product. It has made great contributions to the development of the national economy, but also consumed a large amount of energy and generated environmental pollution [4]. According to previous studies, the activities of the construction industry account for a significantly portions of the world's overall energy consumption [5]. In addition, it contributes to nearly one-third of the global carbon dioxide emissions [6]. Based on the data from the China Energy Statistics Yearbook and the 2022 Research Report of China Building Energy Consumption and Carbon Emissions, from 2005 to 2020, CO_2 emissions from the national construction industry grew at an average annual rate of 6.5%. However, there has been a noticeable increase in energy consumption and carbon dioxide emissions from the construction industry. Additionally, it still accounts for a large proportion of the total national energy consumption and total carbon emissions, as shown in Figures 1 and 2. Therefore, as a major energy consumer, the green development of the construction industry is crucial to the realization of the "dual-carbon" goal. Traditional unrefined development has positioned the relationship between economic growth and environmental pollution in China at the forefront of the environmental Kuznets curve, significantly impeding the high-quality development of the construction industry. Examining the green development of the construction industry will offer vital insights into addressing the fundamental contradiction between economic growth and environmental protection. In today's highly uncertain market and technological environment, how to effectively promote the green transformation of the construction industry has become an urgent and unavoidable question.

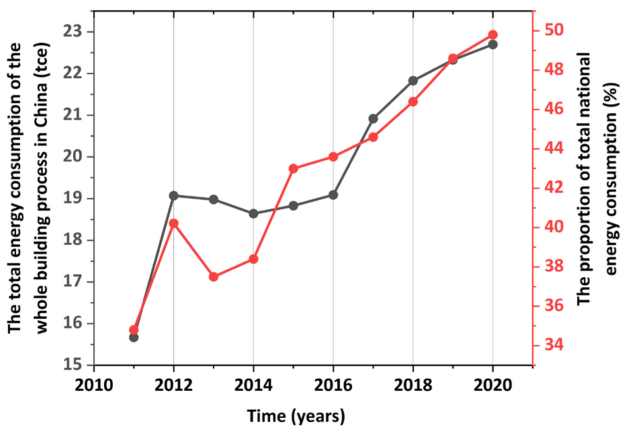

Figure 1. Energy consumption of the entire building process from 2011 to 2020.

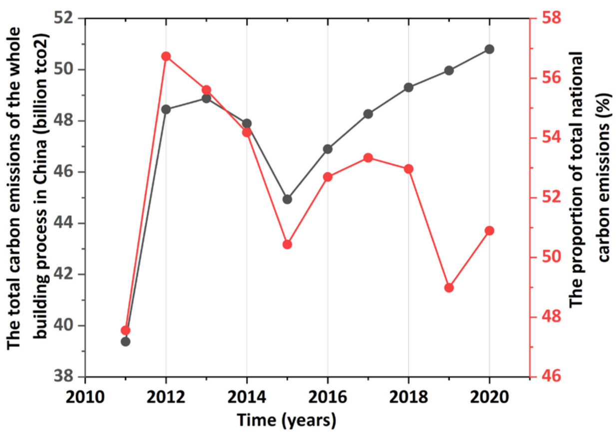

Figure 2. Carbon emission of the entire building process from 2011 to 2020.

As the new phase of the technological revolution develops in an alternative direction, and digitalization and intelligence are the factors considered in the research to be the mainstream decarbonization strategies for high-carbon emission industries [7]. In the field of engineering construction, developed countries have successively presented strategies for the development of the construction industry based on digital technology. Digital technology innovation is used to drive the high-quality development of the construction industry. This has also become an important opportunity and challenge concerning the construction industry in China. Under the "double-carbon" goal, it is necessary to vigorously develop new construction methods represented by greenness, intelligence, and industrialization factors to aid the green development of the construction industry. Practically speaking, the digital transformation of the construction industry emphasizes the following aspects: protecting the environment in the entire process, making the most effective use of limited resources, and minimizing the waste of resources and energy throughout the whole life cycle. In turn, it seeks to save energy and reduce pollution and damage to the ecological environment. Digital transformation promotes the optimization of the allocation of production factors in the production process and pollution control stage of the company, which is conducive to promoting green technological innovation to achieve the greening of the production process, and ultimately promote the green transformation of the construction industry as a whole. The expansion of the new generation of the scientific and technological revolution, as well as the industrial revolution, brought about by automation, artificial intelligence and CNC equipment, and other cutting-edge digital technologies are accelerating the comprehensive penetration and integration of the construction industry, considerably changing the traditional fragmentation of the construction model, breaking the information barriers in various segments. It encourages construction companies to change their production mode, adjust and optimize their industrial structure, provide new development opportunities, and ensure the high-quality development of the construction industry.

Therefore, a fundamental question arises: can the digital transformation of construction companies promote their green development? If it can, what is its intrinsic transmission mechanism? It is of great practical significance to explore how digital transformation strategies empower green development to reduce environmental pollution and achieve a balanced development of economic growth and environmental governance. At present, the digital economy encourages high-quality economic and social development in China, where the relationship between digitalization and green development is gradually being addressed in the research by more scholars. The existing literature mainly focuses on two research perspectives. The first one is the study of the impact of digitization on green development at the regional level. According to the panel data obtained from 281 cities in China, Ma conducted an empirical investigation and determined that the digital economy can directly drive high-quality green development and that industrial structure and green technological innovation are critical mediating mechanisms [8]. With an empirical analysis of 108 cities located in the Yangtze River Economic Belt in China, Luo observed that the digital economy significantly contributes to the efficiency of green development [9]. The second is the exploration of the impact of regional digitization on the green transformation of industries or sectors. For example, Chen systematically examined the impact of the digital economy on green total factor productivity in forestry from the dynamic and spatial dimensions with panel data obtained from 30 provinces in China. The results show a spatial spillover effect on green total factor productivity in forestry in China in the period of 2013–2019, and the digital economy significantly enhances the improvement of green total factor productivity in forestry [10]. Li studied the provincial panel data of China's industry through a spatial model, and the results show that the development level of the digital economy has a spatial spillover effect on the efficiency of industrial green innovation [11]. In summary, it is not difficult to observe that most studies focus on the macro-perspective level. Moreover, confined to the limitations of the data at the micro-company level, there are a lack of studies presenting a micro-perspective in the literature. In fact, company green development can build a resource-saving and environmentally friendly society. Moreover, it is also a necessary way to implement a sustainable development strategy. Therefore, it is particularly important to study the relationship between digital transformation and green development in the construction industry from the micro-enterprise level.

In order to thoroughly explore the relationship and internal mechanism between the digital transformation and green development of construction companies, this paper contributes in the following ways: First, we consider the research perspective. The relationship between digital transformation and green development is explored from the micro level of construction companies as a research perspective. This research theme fits the new normal of "changing production mode, optimizing economic structure, and changing growth momentum" of China's economy. Second, we focus on the research content. The intermediary mechanism between green technological innovation and human capital structure is identified, and the regulatory and threshold effects of environmental regulations are explored. The "theoretical dark box" of digital transformation affecting the green development of construction companies is uncovered.

This paper provides important insights into the future of the achievement of digitization and the "dual carbon" goal. Third, we focus on the research data. In this paper, the digital transformation of construction companies is measured by textual analysis, and green development is measured by the super-efficient SBM model. It enriches the data acquisition methods and ideas of the related research. Unlike in the previous literature, the macro data of the industry or region are selected to explore the relationship between digital transformation and green development. This paper explores this issue in depth by using the micro-data of construction companies as samples. The research conducted on digital transformation and green development in the construction industry remains at the macro-industry level. This paper explores this issue in depth by utilizing the data collected from micro-companies.

The remainder of the paper is arranged as follows: Section 2 presents the theoretical analysis and research hypotheses; Section 3 incorporates the methods and data; Section 4 presents the results; Section 5 presents the discussion; Section 6 consists of the conclusions and implications.

2. Theoretical Analysis and Research Hypothesis

This study analyzed the impact of the digital transformation of construction companies on green development from two perspectives, direct and indirect effects, and proposed the research hypotheses accordingly.

2.1. Digital Transformation and Green Development of Construction Companies

The digital transformation of companies is a form of strategic corporate behavior. At the same time, digitalization is also an important opportunity for companies to create sustainable competitive advantages and break through the technical difficulties of development bottlenecks [12]. Moreover, green development is an inevitable choice for companies' development process. Digitalization is the key strategic means to transform China's construction industry. The digital transformation of companies can drive the improvement of production efficiency; enhance the levels and capabilities of industry, enterprise, and project management; promote the sustainable development of the construction industry to escape from the current predicament. At present, the construction industry must gradually shift from capital-driven high-speed development to digital-driven high-quality development in China. The increasing labor cost, green environment, and the demand for digital city construction are also forcing the digital transformation and upgrading of the construction industry. Under the market competition mechanism, the more digitalized construction companies forced low-value-added and inefficient companies to modernize and optimize their green total factor productivity results through market competition. Due to the continuous penetration of digital technology, companies rely on its accurate information retrieval, collection and analysis, and professional assessment capabilities, and through positioning as well as screening, discover green projects with environmental benefits that combine a more excellent investment value and sound ecology in order to support the implementation of the green transformation of traditional industries, thereby creating more economic benefits. Digital technology promotes the entire construction engineering industry to realize the upgrading and transformation of the whole industry chain from market planning, design, construction, delivery, and operation perspectives. It promotes the construction industry to improve its quality, efficiency, and green development. Additionally, it integrates with other resources to enhance the productivity of companies in all aspects of research and development, design, construction, operation, and maintenance. In addition, the application of digital technology can also instantaneously monitor the ecological environment changes occurring in the production process, effectively reducing the waste of resources and pollutant emissions. The whole chain of the green development of products and processes is realized through the thorough transformation of company production, end pollution treatment, and other elements [13]. With the rapid development of digital technology and the deep integration of the real economy, digital transformation has become a driving force for high-quality economic development. In addition, digitally empowered green transformation is also the process of data resource orchestration. It also realizes the crucial role of data resources as a source of green value creation while improving the efficiency of resource exchange, combination, and integration processes [14].

Based on their business characteristics and traditional advantages, construction companies assess the digital transformation of companies to add to the momentum of green development. Green development in the construction industry focuses on dealing with the relationship between human beings and nature, which aids ecological civilization, resource conservation, and environmentally friendly green construction around the entire construction process. The ultimate goal is the achievement of energy, land, water, and material saving in both design and construction areas. The aim is also to create top-level designs to align the standards to target the treatment, to create a digital industry segment in the digital economy, and to promote digital production R&D manufacturing digital equipment intelligent upgrades, combined with upstream and downstream industries involves in the digital transformation process. Market information asymmetry is the prevalent problem that restricts the green transformation of companies. Therefore, based on the integration of the project BIM digital model and cloud computing, big data, Internet, AI, IoT, VR, GIS, and other technologies, the elements such as "man, material, machine, material, method, environment" and the efficient closed loop formed by engineering planning, execution, inspection, optimization, and improvement are digitally transformed. Through the flow of multi-dimensional construction information, companies can dissolve complexities and uncertainty in the construction process and enhance the economic and social benefits of the project. In turn, this creates the green development of the construction industry with low-energy consumption rates, low pollution, high efficiency, and high quality [15]. Construction companies can use digital technology to improve their production management, integrate the concept of green development into the entire process of production, improve production management efficiency, and thus enhance green and low-carbon development. For example, BIM is used to create value with its visualization via traditional, simulated, and accurate methods. From the optimization of the layout of the building industry in the pre-planning stage, the optimization of green building design based on energy modeling and other spatial optimizations to the optimization of construction drawings and design, the construction site, construction simulation, progress management, and finally to intelligent operation and maintenance management processes based on BIM and other applications, all of these factors represent a single point of value of a small range of savings in resources used to promote the green development of the construction industry [16]. The digital empowerment of green development is viewed from company management informatization and construction business digitization perspectives. On the one hand, the use of "BIM + PM + Cloud" synergy integrates industry chain resources, ensures that each industry chain and participant realizes the whole process of collaborative work and information sharing, improves the construction efficiency and refinement level, reduces the information search and management costs of the construction companies in the production and operation process, revolutionizes the green production mode, and improves the green production efficiency. On the other hand, digital and intelligent construction practices significantly improve the fluency of project implementation and reduce the waste of resources, thus maximizing cost savings and realizing the green development of the construction industry. Accordingly, the following hypothesis is proposed.

H1. *Digital transformation has a significant positive impact on the green development of construction companies*.

2.2. Digital Transformation, Green Innovation, and the Green Development of Construction Companies

Green innovation, also known as environmental innovation, combines traditional technological innovation with ecological concepts [17]. According to the natural resource-based view theory, businesses have essential, unique, controlled resources, and capabilities that create a sustainable competitive advantage [18]. Following this theory, companies must develop specific technological capabilities to overcome more complex environmental technology challenges and achieve sustained green innovation momentum [19]. Digital transformation encourages the green innovation of companies mainly in two ways. On the one hand, digital technology effectively reduces the cost of communication, promotes synergistic cooperation between companies, and drives breakthroughs in complex green key technologies. In addition, it can also improve the efficiency of resource allocation, enhance enterprise growth, and inject strong endogenous power for green innovation [20]. On the other hand, digitalization strengthens the internal connection and breaks the upstream and downstream barriers of companies [21]. The profound use of digitization technology by companies helps to enhance the integration and sharing of R&D information and resources in the enterprise innovation ecosystem. Thus, it enhances the knowledge sharing and integration that occurs between various departments within the enterprise, realizes the fusion and reconstruction of various types of R&D elements, refines new R&D information and knowledge, and ultimately improves the green technology innovation capability of construction companies.

Green innovation is a crucial resource and intermediate link in the green development of companies [22]. Patent applications are easily linked to economic growth, and the complexity of technology and R&D is also negatively correlated with carbon intensity [23]. Therefore, companies, active practitioners of green development, significantly reduce environmental pollution and create higher economic benefits through research and development innovations [24]. Green innovation creates a competitive advantage for companies by promoting their resource integration capability, resource reallocation capability, and environmental insight [25,26]. The improvement of green technology innovation significantly influences the intensity of carbon dioxide emissions of regional construction companies. It affects the level of green development of construction companies [27]. Digital technology innovation at the level of underlying technology service and practical applications has an empowering effect on the high-quality development of the real economy. This creates a series of changes, such as resource release, financing facilitation, industrial upgrading, and efficiency optimization for companies. It also provides more ideas and opportunities for breaking through the bottleneck of green development and realizing green and high-quality development outcomes [28]. With the rapid development of the digital economy, emerging technologies, such as big data and cloud computing, have emerged and matured, promoting digital underlying and application technologies to burst into new vitality at the company level. This has effectively alleviated information asymmetry, reshaped the company operation mode and organizational ecology, and extended to green governance. It significantly reduces the mismatch rate of green innovation factors, thereby promoting the rational allocation of innovation resources and thus improving the level of green technology innovation in companies [29,30]. With digital technology and a new generation of information technology at its core, digitalization provides a good foundation for technological innovation. Then, companies can achieve their strategic goals of resource conservation and environmental protection with a higher level of green innovation through digital technology. According to the signaling theory, the positive signal of being green is indispensable for companies to create sustainable competitive advantages, as it is conducive to financing, winning consumption preferences, and obtaining government support. This promotes the green technology innovation behavior of companies; then, it promotes the overall development of the construction industry. According to the abovementioned analysis, digital transformation provides good conditions for construction companies to conduct green technology innovation, which has apparent positive effects on improving the overall green transformation performance of companies. Correspondingly, the following hypothesis is proposed.

H2. *Digital transformation improves construction company green development total factor productivity by promoting green innovation levels.*

2.3. Digital Transformation, Human Capital Structure, and the Green Development of Companies

The digital transformation of companies inevitably creates a transformation of production methods and relations, which is reflected in the adaptive change in human capital structure in labor–labor relations [31]. As one of the essential factors in the classical economic theory used to explain economic growth, the labor factor has been given importance in theories and models, such as the neoclassical economic growth theory and endogenous growth theory. In firms, human capital is the most critical resource in the organization process. It can be crucial to boosting the competitiveness of companies and accomplishing organizational objectives. The digital transformation of companies affects the structure of human capital, mainly in the demand for skilled labor and the extrusion of part of the less-skilled labor force. On the one hand, digital transformation creates many skilled jobs and strengthens the adsorption capacity of employees with high-level skills working in the company [32]. The technological changes created by digital transformations require more specialized technical talents and R&D professionals. At the same time, the fact that technological R&D is characterized by high-value-added concepts also causes companies to take the initiative to explore this field. Thus, the proportion of technical personnel working in companies increases following digital transformations. The highly qualified human capital also has a stronger innovation ability and better labor productivity, which can play a prominent role in the economic growth and development of companies [33]. On the other hand, in the digital transformation of companies, some less-skilled, repetitive, and replaceable jobs will gradually be replaced by automated machines and equipment. This reduces the demand for less-skilled employees in companies, resulting in a significant reduction in the number of employees performing simple and repetitive tasks [34]. Human capital, as a source of innovation and technological progress, is an effective way to achieve the green transformation of companies [35]. The optimization of the human capital structure improves production efficiency, improves business processes, reduces production costs, and promotes the transformation of products in a green direction. With the improvement of the human capital level in companies, high-quality intellectual capital, and human capital can be integrated into the production and operation processes of products. It produces a direct technology diffusion effect, improves innovation ability, promotes the improvement of production efficiency, and pushes companies toward green development. Highly skilled personnel can improve the production operation efficiency within a company by optimizing the production mode, reducing the inefficiency loss in the production process. This encourages the enterprise to produce items more efficiently. Specifically, the optimization of human capital structure can directly promote the research and development of green equipment and the improvement of existing green cleaning equipment, improve companies' pollution treatment capacity, and promote companies' green development. The lack of talent support in the green transformation development of companies has led to problems, such as the difficult identification of environmental problems, information asymmetry, and an insufficient basis for strategic decision-making behavior [36]. Moreover, the demand for highly skilled personnel caused by digital transformation has optimized companies' human capital structure, effectively solving various problems caused by the need for more skilled employees. This promotes the green development of construction companies.

H3. *Digital transformation improves construction company green development by optimizing the human capital structure.*

2.4. Digital Transformation, Environmental Regulation, and the Green Development of Companies

Environmental regulation, a way of realizing environmental protection by regulating all kinds of behaviors that pollute the environment, is a kind of control and intervention strategy used by the authorities of companies to protect the environment and save resources. The construction industry, a traditional high-loss, high-pollution, and high-emission industry, are undoubtedly subject to the constraints and influences of environmental regulations. Specifically embodied in first, environmental regulation presents the "innovation compensation" effect. In the context of environmental regulations, companies improve the levels of technology and more innovative activities, improve the long-term competitiveness of companies, and offset the increase in costs due to the levy of pollution fees in favor of the green development of construction companies [37]. Secondly, the environmental protection awareness of a company is enhanced, and it will pay more attention to green sustainable development at the level of production and operation. At this time, the occurrence of digital transformations to improve the role of enterprise green technology innovation is more remarkable, which in turn can better promote enterprise energy saving and emission reduction rates [38]. Finally, environmental regulations can encourage the construction industry to produce a "competition effect". The implementation of environmental regulations changes the number and size of the construction industry in the region. It encourages the construction industry to generate power to result in a digital transformation. In order to seek better development results, construction companies can promote the implementation of reforms, improve efficiency, reduce pollution, and achieve green development. Accordingly, the following hypothesis is proposed.

H4. *Environmental regulations have a moderating effect between digital transformations and construction company green development outcomes.*

2.5. Digital Transformation, Human Capital Structure, and the Green Development of Companies

As an external regulatory mechanism, environmental regulation is the primary driver of corporate environmental behavior [39]. It is the internalization of losses produced by the external environment in the production activities of a firm into the costs of the firm [40]. It creates momentum for digital transformation and impacts the digital empowerment of the green development of construction companies. When environmental regulation behavior is weak, it fits the "compliance cost" effect. As the cost borne by companies for environmental pollution is low, it leads to a relatively reduced willingness of the companies to create technological innovations for digital transformation processes. As the intensity of environmental regulations increases, the cost of pollution exceeds that of governance, which is consistent with the "innovation compensation" effect. At this time, companies will be forced to perform green innovation activities, the digital transformation of production equipment, and processes. High environmental regulations prevent companies from using many resources to cope with environmental requirements so that innovation resources are excluded. Therefore, this paper argues that only in the optimal range of environmental regulations can the effect of promoting the digitalization of construction companies to enable green development be maximized. Accordingly, the following hypothesis is proposed.

H5. *Environmental regulation intensity presents a threshold effect between digital transformation and construction company green development.*

The theoretical mechanism analysis framework of this study is presented in Figure 3.

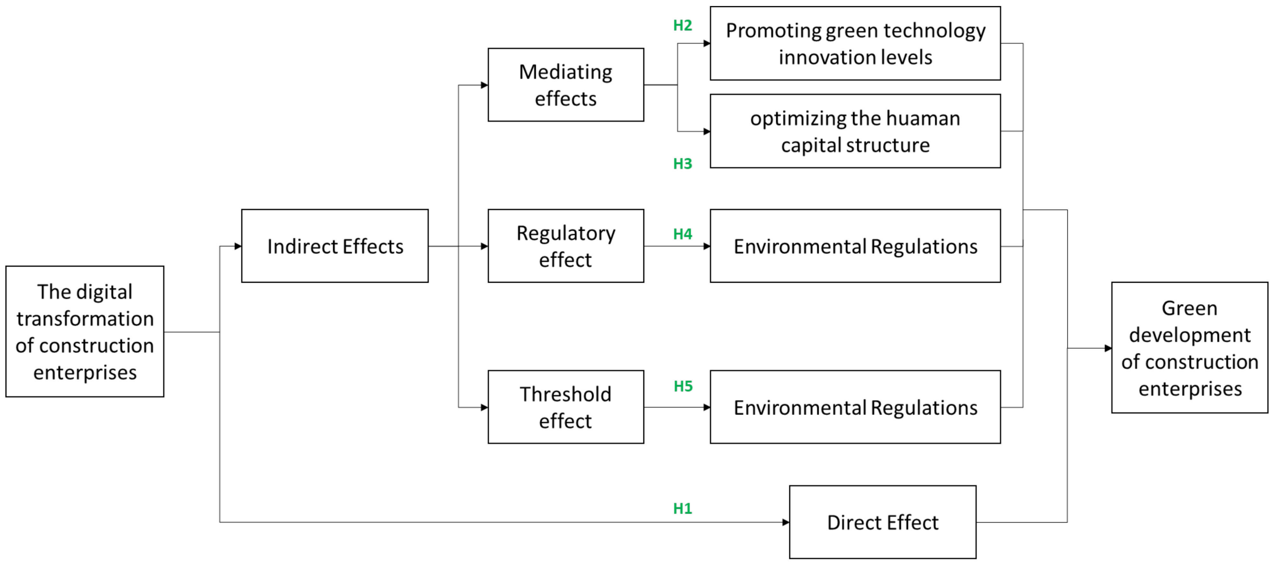

Figure 3. Theoretical mechanism analysis framework.

3. Research Design

Through theoretical analysis, the digital transformation of construction enterprises can either directly enhance or indirectly promote the green development of enterprises by improving green technological innovation and optimizing human capital structure. In addition, environmental regulation presents a moderating effect on the digital transformation of construction enterprises, and there may be a threshold effect. This section describes the acquisition of data sources and the model we used. In the subsequent section, this study empirically investigates the direct and indirect relationships between the digital transformation and green development of construction enterprises through econometric analysis methods.

3.1. Research Model

To empirically examine the abovementioned research hypotheses, this paper constructed the following model:

$$GD_{i,t} = \alpha_0 + \beta_1 DCG_{i,t} + \beta_2 Controls_{i,\,t} + \sum Firm_i + \sum Year_t + \varepsilon_{i,\,t}. \quad (1)$$

In model (1), the subscripts i and t denote firms and years, respectively. GD measures the level of digital transformation of the companies, which is the explanatory variable; DCG, which represents the green development of the firm, is the core explanatory variable; Controls are the control variables of the paper; ε is the model random error term. To enhance the reliability of the regression results and absorb the fixed effects as much as possible, this paper controls for both time (Year) and industry (Firm) dummy variables.

3.2. Sample and Data Sources

This paper selected the research sample that listed the Shanghai and Shenzhen A-shares in the construction industry in China from 2015 to 2021. Due to the data availability and ensuring data accuracy, 57 construction firms were finally selected as the samples used for this study. ST, ST*, suspension, and delisting samples were not included. The primary sources of the pertinent data were the CSMAR database, "China Statistical Yearbook", "China Energy Statistical Yearbook", and corporate annual reports of companies. The definition and metrics of specific variables presented in this paper were as follows.

3.2.1. Independent Variable: Company Digitalization

Measuring the digitalization level of construction companies is significant for identifying barriers to the development and existing problems in the construction industry. In construction companies, since most of the articles on the digital transformation at present remain on a theoretical basis, there more measurements of digital transformation indicators are required. This study used the textual analysis to measure digital transformation by referring to Wu's study [29]. The vocabulary in the annual reports of companies is frequently considered to reflect the strategic characteristics and future outlook of companies, thus reflecting the business philosophy and development path of the companies in order to better reflect the extent of their digital transformations. Therefore, Python 3.7 was used to capture the keywords related to digital transformation presented in the annual reports of companies and to calculate the frequency of word occurrences. Among them, the sources of keywords referred to Tu's method. Specifically, the selection method was used to combine the existing literature on the topic of the digital transformation of companies; refer to the relevant policy documents and research reports on the digital transformation of the construction industry, such as "Uniform Standard for Building Information Model Application", "Opinions of the General Office of the State Council on Promoting the Sustainable and Healthy Development of the Construction Industry and Healthy Development of the Construction Industry", and "Outline of Information Development in the Construction Industry from 2016 to 2020"; artificially select a sample of companies that were more successful in their digital transformations; judge and extract the keywords of digitization from their annual reports [41]. Finally, invalid text content, not obtained from our company, was excluded with the help of Python's text recognition function, and keyword expressions with negative lexical prefixes were also excluded. In addition, due to the considerable differences in the size of companies, the frequency of occurrence of the abovementioned keywords was not of comparative value. To solve this problem, this paper referred to the method of Ren and adopted the ratio of the frequency of keyword occurrences of companies in the year and the total frequency of occurrences of companies in the construction in year as the metric [42], specifically, as calculated in Equation (2), where $\mathrm{keyword}_{i,t}$ represents the frequency of keyword occurrences of the company in year t, and $\mathrm{totalkeyword}_t$ indicates the total frequency of keyword occurrences of all construction companies in the sample volume.

$$\mathrm{DCG}_{i,t} = \frac{\mathrm{keyword}_{i,t}}{\mathrm{totalkeyword}_t}. \tag{2}$$

3.2.2. Dependent Variable: Green Development

1. Measurement Method

Since the Solow model was proposed in the literature, total factor productivity has been widely used to assess production efficiency. However, traditional productivity calculations focus only on the positive effects, ignoring the negative impacts of production on the environment. Green total factor productivity is proposed to measure the real production efficiency considering the cost of resources and the environment and objectively reflect the degree of green development by incorporating resource consumption and environmental pollution into the analytical framework of production efficiency.

Tone [43] proposed a non-radial non-angle SBM (slack-based measure) model, where the slack variables were directly incorporated into the objective function to measure the inefficiency from input and output perspectives. However, this model did not consider the undesired output, and the calculated productivity was prone to great deviations. The production of wastewater, exhaust, and solid waste non-desired outputs in the actual production process, as well as the inability of the traditional SBM model to perform additional distinctions between effective decision-making units. Therefore, the proposal of the super-efficient SBM model helped to solve this problem. We adopted the research method of Jahanshahloo [44] and chose the super-efficient SBM model with non-expected output results to measure the green total factor productivity of the construction industry in this paper. Malmquist was widely used in the panel efficiency analysis. To support the analysis of non-desired outputs, the Malmquist–Luenberger (ML) index introduces the directional distance function into Malmquist. This effectively solves the problem of planning without feasible solutions by including the production units in the global reference set and constructing the global-Malmquist–Luenberger (GML) index. In summary, the combination of the SBM model considering non-expected outputs and the GML index to measure the GTFP not only addressed the shortcomings that the traditional DEA method does not compare across periods, but also avoided the problem of the ML index not presenting a feasible solution for the decision unit. Therefore, an index system containing inputs, desired outputs, and non-desired outputs was constructed to measure the green development effect of construction companies and their dynamic growth. The specific of the measurements were as follows: [45] assume that each company is a production decision unit, $DMU_j(j = 1, 2, \ldots\ldots, n)$, and each production decision unit includes three vectors of input x, desired output y^1, and non-desired output y^2, thus defining the following finite set of production possibilities:

$$P\Big|(x_0, y_0) = \left\{ (\,\overline{x} \geq \textstyle\sum_{k=1}^{n} \lambda_k\, \overline{x}_k,\ \overline{y}^1 \leq \sum_{k=1}^{n} \lambda_k\, \overline{y}_k^1,\ \overline{y}^2 \leq \sum_{k=1}^{n} \lambda_k\, \overline{y}_k^2,\ \lambda \geq 0 \right\}. \quad (3)$$

Assuming that there are u inputs, $x \in R^u$, $y^1 \in R^{m1}$, $y^2 \in R^{m2}$, x_{ik}, y_{ik}^1, and y_{ik}^2 are the slack values for the inputs, desired outputs and undesired outputs, respectively. The super-efficient SBM model with the non-desired outputs taken into account is illustrated below:

$$\min\beta = \frac{\frac{1}{u}\sum_{i=1}^{u}\left(\frac{\overline{x}_i}{x_{ik}}\right)}{\frac{1}{m_1+m_2}\left(\frac{\sum_{r=1}^{m_1}\overline{y}^1}{y_{ik}^1} + \frac{\sum_{r=1}^{m_1}\overline{y}^2}{y_{ik}^2}\right)},$$
$$\text{s.t.}\begin{cases} \overline{x} \geq \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j \\ \overline{y}^1 \leq \sum_{j=1,j\neq k}^{n} y_j^1\lambda_j \\ \overline{y}^2 \leq \sum_{j=1,j\neq k}^{n} y_j^2\lambda_j \\ \overline{x} \geq x_0 \\ 0 \leq \overline{y}^1 \leq y_k^1 \\ \overline{y}^2 \geq y_k^2 \\ \sum_{j=1,j\neq k}^{n} \lambda_j = 1, \lambda \geq 0 \end{cases} \quad (4)$$

In Equation (4), β is the target efficiency value, λ denotes the weight, and subscript k is the decision unit being evaluated. β is strictly monotonically decreasing with respect to m-, m_1, m_2, and satisfies $0 < \beta < 1$. The decision unit is valid only when $\beta = 1$ and m-, m_1, $m_2 = 0$ for a given decision unit. Solving the super-efficient SBM model under the current period production possibility set can be obtained:

$$\overline{D}_0^G\left(x^t, y^t, b^t; y^t, -b^t\right). \quad (5)$$

By the directional distance function derived from the abovementioned super-efficient SBM, the GML index from period t to t + 1 is [46]:

$$GML_t^{t+1} = \frac{1 + \overline{D}_0^G\left(x^t, y^t, b^t; y^t, -b^t\right)}{1 + \overline{D}_0^G\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}. \quad (6)$$

GML_t^{t+1} represents the green total factor productivity index of the construction industry. That is, the level of green development in the construction industry from period t to t + 1 in this paper.

2. Data Description

The goal of green development is to promote the continuous improvement of green total factor productivity; therefore, most scholars agree that green total factor productivity measures green development [47]. In this paper, the super-efficient SBM and GML index models were used to measure the green development level of construction companies. In addition, since this paper measured green development from a low-carbon perspective, carbon dioxide was chosen as the non-expected output. Each indicator was specifically chosen, as presented in Table 1. Among them, the data of capital input, labor input, and total income could be directly obtained from CSMAR. However, the data of the energy input and non-expected output for construction companies were not directly available.

Table 1. GTFP index measurement index system.

Type of Indicator	Indicator Name	Indicator Meaning	Measurement Method
Input Indicators	Capital input	Net fixed assets of construction companies	Direct statistics
	Labor input	Number of employees in construction companies	Direct statistics
	Energy input	Energy input of construction companies	(An company main business cost/construction industry main business cost) × construction industry all kinds of energy end consumption of physical amount converted into "standard coal" summary into total energy consumption
Expected output	Total revenue	Total revenue of construction companies	Direct statistics
Non-expected output	Carbon dioxide emission	CO_2 emissions from construction companies	(An company main business cost/construction industry main business cost) × Estimated amount of CO_2 emissions

This paper referred to Liu's study and estimated the data by multiplying the weights of the main operating costs in companies as a percentage of the construction industry [48]. Among them, the estimated amount of CO_2 emissions from the construction industry was based on the consumption of eight types of primary energy sources in the "China Energy Statistics Yearbook", except for electricity consumption. The CO_2 emissions were estimated based on the number of burns and default emission factors as detailed in IPCC (2006) [49]. The specific formula is displayed below:

$$C = \sum_{i=1}^{8} C_i = \sum_{i=1}^{8} E_i \times NCV_i \times CEF_i \times COF_i \times \left(\frac{44}{12}\right) \times CE_i. \quad (7)$$

In the formula, C stands for carbon dioxide emissions, i = 1, 2, 3, . . . , 8 indicates the type of primary energy, and E, NCV, and CE respectively represents energy consumption, average low-level heat of energy, and standard coal coefficient factors. These data were obtained from the "China Energy Statistical Yearbook" and "General Rules for Calculating Comprehensive Energy Consumption". CEF is the amount of carbon contained per unit calorific value obtained from the "Guidelines for Provincial Greenhouse Gas Inventories", and COF is the carbon oxidation factor obtained from the "IPCC Guidelines for National Greenhouse Gas Inventories". The values of 44 and 12 are the molecular weights of carbon dioxide and carbon, respectively. The specific reference coefficients are presented in Table 2, and other raw data were obtained from the "China Statistical Yearbook", "China Energy Statistical Yearbook", and CSMAR.

Table 2. Referential coefficients of carbon emission estimates for various primary energy sources.

Energy Source	Average Calorific Values per Unit (MJ/kg)	Carbon Emission Coefficients (kgc/MJ)	Carbon Oxidation Factor	Conversion Factor (kg Standard Coal)	Carbon Emission Factor (Ton Carbon/Ton Standard Coal)
Coal	20.934	0.02637	1	0.7143	0.7559
Coking coal	28.470	0.0295	1	0.9714	0.8550
Crude Oil	41.868	0.0201	1	1.4286	0.5857
Gasoline	43.124	0.0189	1	1.4571	0.5538
Diesel	42.705	0.0202	1	1.4571	0.5921
Fuel Oil	41.868	0.0211	1	1.4286	0.6185
Natural Gas	38.979	0.0153	1	1.33	0.4483
Kerosene	43.124	0.0196	1	1.4714	0.5714

Note: (1). The unit of natural gas to standard coal factor is kgce/m^3; (2). The coefficients in the table are from the "IPCC Guidelines for National Greenhouse Gas Inventories"; (3). According to GB/T3102.4 International Steam Table Card Conversion, a fuel with a low-level heat content equal to 29.3076 MJ [7000 kcal (kcal)] is called 1 kg of standard coal (1 kgce).

3. Analysis of Measurement Results and Situation at Present

In accordance with the abovementioned theoretical methods and indicators, this paper quantified the relevant indicators. It estimated the changes in green total factor productivity of construction companies considering carbon dioxide emissions as a non-desired output based on MATLAB 2016a. This article lists an overview of the green development of the construction industry as a whole on annual basis. The green total factor productivity of the construction industry presents an upward trajectory from 2015 to 2021, as depicted in Figure 4. Due to the vigorous development of digitization, greening, and low-carbon transformation, the growth rate significantly accelerated after 2020. In addition, from the trend of its decomposition term, the changes in the GML index after 2015 overlapped with the changes in the GTC index, indicating that the improvement of green total factor productivity in the construction industry was mainly due to the improvement of technological progress, while there is still plenty of room for the improvement of technical efficiency in the construction industry at present.

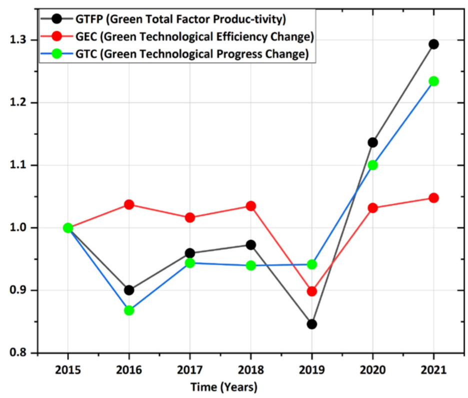

Figure 4. Trends of GTFP and its decomposition term in China's construction industry from 2015–2021.

3.2.3. Mediator Variable

This paper explored the influence mechanism from two aspects: green innovation and human capital. On the one hand, the logarithm of green patent applications (GTI) measures green innovation. The application for green patents has a high technical threshold, with requirements in R&D, promotion, and application. In addition, the reason for selecting the number of applications instead of grants was that the number of green patent applications intersected with grants eliminating the time lag and making it easier to understand the green technology innovation in the current year [50]. On the other hand, in the mechanism test of human capital, the percentage of staff with bachelor's degrees and higher in the samples of construction companies, which are located in 31 provinces of China, (LaborStruct) was used as the mediating variable [51]. This was because the level of education of the labor force could reflect the level of skills, and the work performed by highly educated employees or their positions usually require a higher level of skills. In contrast, the work performed by employees with a low level of education was generally routine and highly replaceable [52].

3.2.4. Moderating Variable

In this paper, environmental regulation was used as a moderating variable. To more effectively reflect the intensity of environmental regulations in the region where the companies were located, this paper used the word frequency ratio of 27 environmental words to the government work reports at the local and municipal levels as a form of measurement [53].

3.2.5. Control Variables

In this paper, referring to the previous studies, we mainly controlled for variables related to the nature of the firm and corporate governance, as follows: firm age (Age), nature of equity (SOE), current ratio (CR), equity concentration (Cocen), total asset turnover (ATO), and return on equity (ROE). The detailed definitions and descriptions of the variables in this study are provided in Table 3.

Table 3. Variables definition.

Variable Type	Variables	Variable Symbols	Variable Description
Dependent variable	Green development	GD	Super-efficient SBM model and GML index method
Independent variable	Company Digitalization	DCG	The frequency of digital transformation keywords in the year of companies/the total frequency of digital transformation keywords in the year of construction industry
Mediator variables	Green innovation	GTI	The number of green patent applications of the enterprise in the year plus 1 to take the logarithm
	Human capital structure	LaborStruct	Percentage of personnel with bachelor's degree or above in companies
Control variables	Company age	Age	Current year—year of launch + 1
	Nature of shareholding	SOE	Dummy variables, state-owned companies take the value of 1, non-state-owned companies take the value of 0
	Liquidity Ratio	CR	Total current assets/total current liabilities
	Equity concentration	Cocen	Shareholdings of top 10 shareholders
	Total asset turnover	ATO	Operating income/average total assets
	Net asset yield	Roe	Net income/average net assets

4. Empirical Results and Analysis

4.1. Descriptive Statistical Analysis

Descriptive statistics were analyzed for the study's main variables of samples, and the results are presented in Table 4. It can be observed that the standard deviation of the green development level of 57 construction companies is 0.051, the minimum value is 0.829, and the maximum value is 1.244. These data indicate a particular gap between the green development practices of different companies. From the perspective of the digital transformation of companies, the mean value was 0.018 and the standard deviation was 0.030. This shows that the digitalization level of companies needs to be improved. Additionally, there is a large gap in the degree of digital development between individual companies. The minimum value of green innovation is 0, and the standard deviation is 1.122, which demonstrates a significant difference in the level of green innovation between companies, and the overall mean value is less than 1, expressing that the overall level of green innovation is relatively low.

Table 4. Descriptive statistical analysis.

Variable Name	Abbreviations	Observation	Mean	SD	Min	Max
Green development	GD	379	1.033	0.051	0.829	1.244
Company Digitalization	DCG	379	0.018	0.030	0	0.235
Green innovation	GTI	379	0.845	1.122	0	5.288
Human capital structure	Laborstrcut	379	0.452	0.155	0.101	0.834
Company age	AGE	379	22	5.961	7	38
Nature of shareholding	SOE	379	0.544	0.499	0	1
Liquidity Ratio	CR	379	1.322	0.424	0.477	5.300
Equity concentration	Cocen	379	0.583	0.162	0.216	1
Total asset turnover	ATO	379	0.620	0.316	0.023	2.977
Net asset yield	ROE	379	0.016	0.059	−0.484	0.211

4.2. Correlation Analysis

The results of Pearson's correlation test for the main variables are presented in Table 5. Digital transformation is significantly and positively correlated with green innovation, human capital, and the explanatory variable presented in this paper, enterprise green development, indicating that the digital transformation of construction companies can promote the green development of companies, which initially verifies the hypothesis of this paper. Moreover, the correlation coefficients of all variables were below 0.7. For this reason, this paper used the variance inflation factor VIF analysis to test the covariance of all the variables in the model, and the VIF values were less than five, indicating no multicollinearity among the variables.

Table 5. Correlation analysis.

Variable Name	GD	DCG	GTI	Laborstruct	AGE	SOE	CR	Cocen	ATO	Roe	VIF
GD	1.000										
DCG	0.209 ***	1.000									1.23
GTI	0.220 ***	0.348 ***	1.000								1.22
Laborstrcut	0.145 ***	0.102 **	0.180 ***	1.000							1.10
AGE	0.119 **	−0.104 **	−0.104 **	−0.191 ***	1.000						1.29
SOE	0.045	−0.228 ***	−0.120 **	0.116 **	−0.280 ***	1.000					1.21
CR	−0.029	0.040	−0.025	−0.053	0.123 **	−0.139 ***	1.000				1.07
Cocen	0.030	0.080	0.179 ***	0.088 *	−0.341 ***	0.088 *	−0.179 ***	1.000			1.21
ATO	−0.091 *	−0.011	−0.070	0.075	−0.039	0.044	0.079	0.097 *	1.000		1.04
ROE	−0.076	−0.113 **	−0.062	0.115 **	−0.106 **	0.011	−0.049	−0.019	0.057	1.000	1.06

Note: ***, **, and * indicate 1%, 5%, and 10% respectively.

4.3. Benchmark Regression

In order to select the appropriate regression method, Hausman tests were conducted for the models, and the test results indicate that the fixed-effects model is more appropriate. Additionally, the firm and time effects were further controlled in the regressions to absorb the fixed effects as much as possible. In order to select the appropriate regression method, the Hausman test was conducted for all models, and the test results show that the fixed-effect model is more suitable for this study.

In this paper, we conducted a benchmark effect test for the principal regression, the empirical regression test of "digital transformation and green development of construction companies". The regression results of the empirical model are presented in Table 6. Along the lines of empirical research, first, the dummy variables of firm and time were controlled and regressed (column 1), and the control variables were included in the subsequent tests (column 2). The results show that the coefficient of the effect of digital transformation on the green development of construction companies is significantly positive (β = 0.878, $p < 0.01$). Second, the control variables were added to the model. The study results show that digital transformation is still significantly positively related to green development, which is significantly positive at the 1% level. Hypothesis H1 was supported.

Table 6. Benchmark regression.

Variable Name	GD	GD
	1	2
DCG	0.878 *** (6.62)	0.775 *** (5.89)
AGE		−0.077 *** (−2.92)
SOE		0.0003 (0.02)
CR		0.021 ** (2.44)
Cocen		0.147 *** (3.69)
ATO		−0.013 * (−1.65)
ROE		−0.026 (−0.61)
_cons	1.028 *** (57.39)	2.652 *** (4.51)
Time FE	YES	YES
Firm FE	YES	YES
Obs	379	379
R^2	0.2628	0.3172

Note: T-statistics are shown in parentheses. ***, ** and * indicate 1%, 5% and 10% respectively.

4.4. Endogenous Problems

4.4.1. Instrumental Variables Method

Although the abovementioned analysis determined a correlation between digital transformation and green development in construction firms, further identifying that a causal relationship was required. In the empirical study presented in this paper, there may have been an endogeneity problem due to reverse causality, where firms with a higher level of green development were more inclined to undergo a digital transformation. Realistically, the green development of companies and low-carbon emission reductions require substantial investments in capital and technical equipment. Hence, companies better at energy conservation and emission reduction measures usually have greater financial and technological strengths, which may further strengthen their incentives to continue with digital transformation practices. The resulting reverse causality problem can lead to a biased estimation of the core parameters. Therefore, this paper adopted the instrumental variable approach to address endogeneity due to the reverse causation effect. First, considering that there may be a time lag in the impact of corporate digital transformation, we reran the regression with the core explanatory variables lagged by one period, and the results are presented in column 1 in Table 7 [24]. It can be observed that the coefficient estimation for the digital transformation of firms remains significantly positive at the 1% confidence level. Second, this paper referred to constructing instrumental variables in Tu. The core explanatory variables with one period lag were instrumental for endogeneity testing [41]. The results are presented in column 2 in Table 8, which shows a significant positive correlation between the digital transformation of companies and green development. From the abovementioned results, it can be observed that the conclusion does not produce a significant change.

Table 7. Instrumental variables method.

Variable Name	Frist Stage	Second Stage
	DCG	GD
	1	2
DCG		0.6405 ** (2.53)
L.DCG	0.5492 *** (3.90)	
_cons	0.4944 *** (3.85)	3.6250 *** (3.87)
Controls	YES	YES
Time FE	YES	YES
Firm FE	YES	YES
Obs	323	323
R^2	0.7302	0.4120

Note: T-statistics are shown in parentheses. *** and ** indicate 1% and 5%, respectively.

Table 8. Propensity score matching (PSM) method.

Variable Name	Instrumental Variables		PSM
	Stage 1	Stage 2	
	DCG	GD	GD
	1	2	3
DCG		2.51 ** (2.20)	0.8154 *** (5.73)
Port	0.0074 ** (2.38)		
_cons	−0.01510 (−0.06)	1.7689 ** (2.19)	0.7306 *** (14.90)
Controls	YES	YES	YES
Time FE	YES	YES	YES
Firm FE	YES	YES	YES
Obs	379	379	369
R^2	0.6869	0.1049	0.3056

Note: T-statistics are shown in parentheses. *** and ** indicate 1% and 5%, respectively.

Moreover, the number of Internet broadband access ports was selected as an instrumental variable by referring to the idea of the study conducted by Xie [54]. The regression results are presented in columns 1 and 2 in Table 8. On the one hand, in the first stage, the regression coefficient of Port and DCG is 0.0074, which is significant at the 5% level. This suggests that the higher the number of regional Internet broadband access ports, the more this encourages firms to perform digital transformations, satisfying the instrumental variable correlation assumption; the F-statistic was greater than 10, rejecting the hypothesis of a weak instrumental variable. The results of the second stage show that the digital transformation of companies can significantly facilitate them to conduct green development activities, which again verifies the validity of the regression results.

4.4.2. Propensity Score-Matching (PSM) Method

The propensity score-matching method can effectively reduce the endogeneity bias resulting from the sample selection problem. As the more significant and financially sound companies are more capable of digital transformations, green development is greater. Thus, it is highly possible that there will be a sample selection bias problem. In order to overcome the endogeneity bias caused by the sample selection problem and to exclude the influence of the inherent characteristics of the sample firms on the results, this paper used PSM to regress the experimental and control groups and adopted the 1:1 nearest-neighbor matching method to match the propensity scores and empirically analyzed the results of the matching process. The specific grouping divided the sample into treatment and control groups according to the degree of enterprise digital transformations. This paper divided the degree of enterprise digital transformation greater than the sample means as the treatment group; otherwise, it was the control group. On this basis, the control variables were matched on the propensity score.

Figure 5 presents the probability density distributions of the treatment and control groups prior to matching. Then, Figure 6 expresses the probability density distributions of the out-treatment and control groups following matching. The results present a significant difference between the pre-matching treatment and the control groups, and the probability densities between the post-matching treatment and control groups almost overlap. This indicates that the matched-sample treatment and control groups are better fitted. Figure 7 demonstrates that the samples after matching are almost within the common range of values. Consequently, the two sets of samples are more similar after matching. From the abovementioned results, we concluded that the treatment and control groups are more similar after matching, which indicates that the matching is effective. Figure 8 shows that most variables' standardized deviations (%bias) after matching are less than 5%. This proves that the matching results are credible. Finally, this paper uses a regressed model (1) again with the matched new samples, and the regression results are presented in column 3 in Table 8. As shown by the results, the regression results remain stable and the coefficient of the digital transformation of companies (DCG) is significantly positive at the 1% level. It illustrates that the results remain robust after the sample self-selection bias problem.

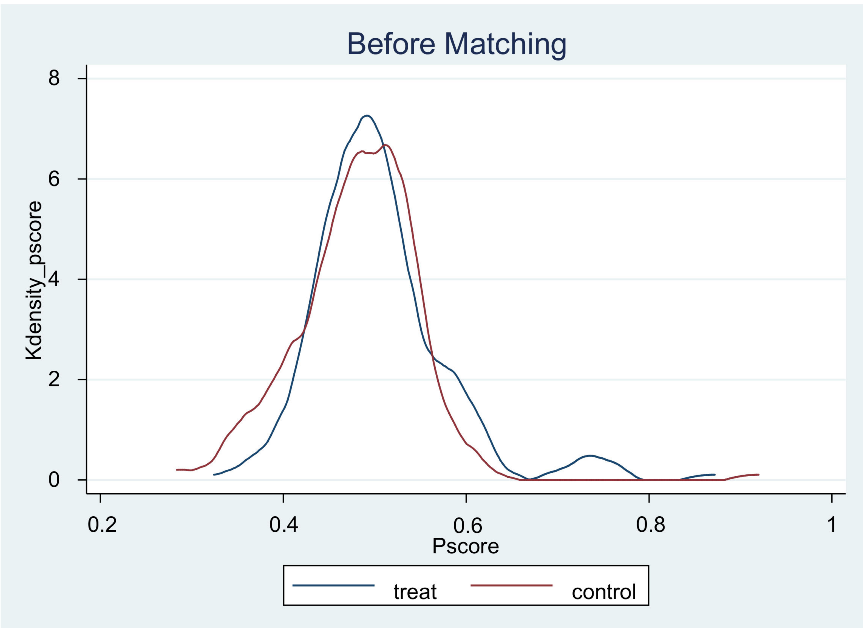

Figure 5. Kernel density function plot before matching.

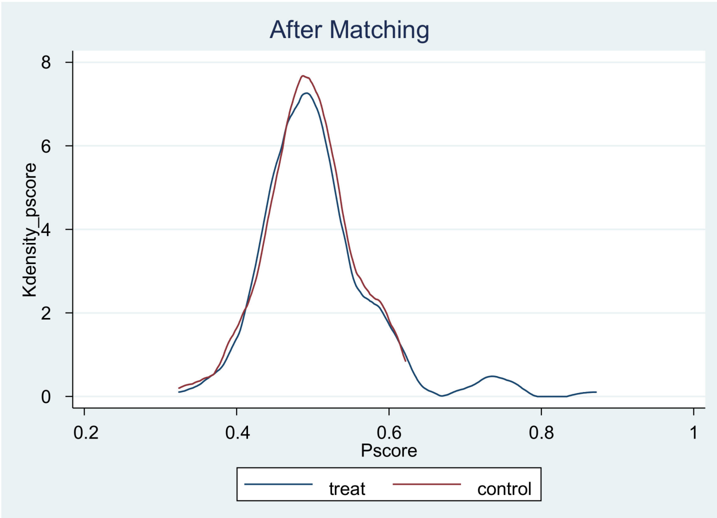

Figure 6. Kernel density function plot after matching.

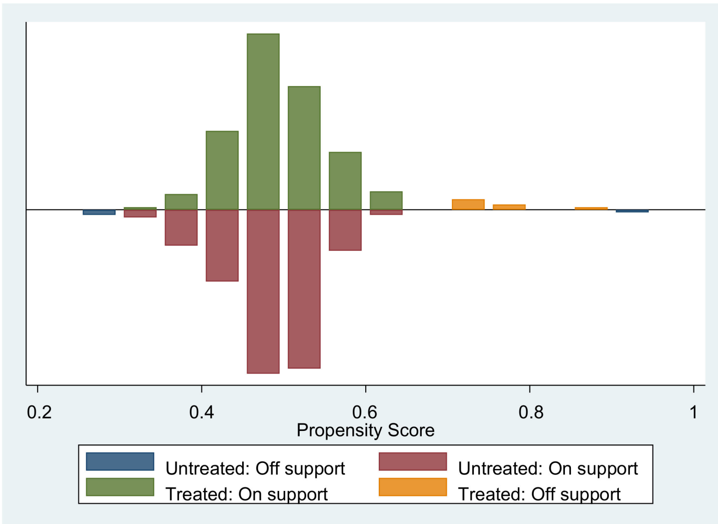

Figure 7. Common range of values of propensity scores.

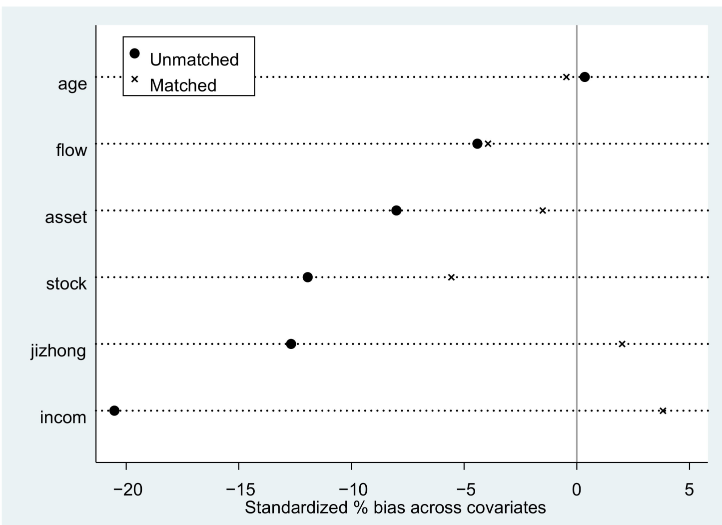

Figure 8. Standardized deviation before and after matching.

4.5. Robustness Tests

In order to test the reliability of the empirical results, this paper used a total of three methods for robustness testing: variable substitution, model test method substitution, and lag one period. The results are still consistent with the expectations, indicating that this study has robustness.

1. Variable replacement.

First, this paper adopted the approach of replacing the core explanatory variable. The total word frequency of the digital transformation was used to take the natural logarithm (lnDig) to replace the core explanatory variables, which were entered into the original model and retested [55]. The specific regressions are presented in column 1 in Table 9, and the results indicate that the findings remain robust after changing the measure of enterprise digital transformation.

Table 9. Robustness test.

Variable Name	Variable Replacement	Model Test Method Replacement	Lag Regression
	GD	GD	GD
	1	2	3
DCG		0.448 *** (5.05)	
lnDig	0.032 *** (8.00)		
L. DCG			0.352 ** (2.05)
_cons	1.637 *** (2.78)	0.976 *** (48.25)	3.366 *** (4.44)
Firm FE	YES	NO	YES
Year FE	YES	NO	YES
Obs	379	379	379
R^2	0.3705	—	0.1893

Note: T-statistics are shown in parentheses. *** and ** indicate 1% and 5% respectively.

2. Model test method replacement.

To enhance the robustness of the results, the Tobit model was used for the regression. The reason for selecting this model was that the GTFP values measured by the super-efficient SBM model were within (0, +∞), which is typical of truncated data. Therefore, according to Wang, the panel Tobit model was selected for robustness testing, which was suitable for the regression analysis of truncated data [56]. The results presented in column 2 in Table 9 demonstrate that the independent variable's regression coefficient is significantly positive with a coefficient of (β = 0.448, p < 0.01), which is consistent with the results of the benchmark regression. The results presented in column 2 in Table 9 show that the regression coefficient of the independent variable is significantly positive (β = 0.448, p < 0.01), consistent with the results obtained for the benchmark regression.

3. Lag regression.

The digital transformation of companies from input to value output must be subjected to a specific time period, and the coupling and even integration of digital technology and the real economy can be realized only after continuous debugging. Therefore, the impact of digital transformation on the green development efficiency of companies may present a time lag. Furthermore, this paper lagged the core explanatory variables by one period to analyze the time lag effect. The results are presented in column 3 in Table 9, and the results remain robust.

4.6. Heterogeneity Analysis

4.6.1. Heterogeneity Test Based on Micro-Characteristics of Firms

Firstly, based on the micro-characteristics of companies, this paper divided the samples into state-owned and non-state-owned according to the nature of their ownership. The results are presented in columns 1 and 2 in Table 10. Digital transformation can significantly improve green development in state-owned and non-state-owned companies; however, the enhancement effect is relatively greater in state-owned companies. This is because digital transformation requires the widespread application of digital technologies, large-scale investments in digital construction, and the building of modern information systems. This provides SOEs with greater advantages in capital, scale, research, and policy areas. These benefits enable them to better implement digital transformation, realize the organic combination of digital strategies and enterprise advantages, and promote high-quality development.

Table 10. Heterogeneity analysis.

Variable Name	**State-Owned Enterprises**	**Non-State-Owned Enterprises**	**Large Companies**	**Small and Medium-Sized Enterprises**	**High Development Level of Digital Economy**	**Low Development Level of Digital Economy**
	GD	**GD**	**GD**	**GD**	**GD**	**GD**
	1	**2**	**3**	**4**	**5**	**6**
DCG	1.00 *** (5.20)	0.824 *** (4.20)	1.7672 *** (5.36)	0.6203 *** (4.10)	0.632 *** (3.48)	0.911 *** (4.57)
_cons	0.768 *** (11.81)	0.557 *** (6.68)	0.8237 *** (14.25)	0.6150 *** (9.37)	0.7311 *** (9.55)	0.651 *** (9.42)
Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	201	178	159	220	189	190
R^2	0.3812	0.3314	0.3638	0.3882	0.2974	0.3880

Note: T-statistics are shown in parentheses. *** indicate 1%.

Secondly, according to the “Measures for Classifying Large, Small, Medium, and Micro Companies in Statistics” (2017) issued by the “National Bureau of Statistics”, this paper classified construction companies into large, small, and medium-sized companies. Specifically, the construction companies that simultaneously meet a business revenue higher than or equal to 80,000 and total assets higher than or equal to 80,000 were classified as large companies, and the rest were categorized as small- and medium-sized companies. From the results presented in columns 3 and 4 in Table 10, it can be observed that the role of digital transformation used to enhance green development is more significant in large companies. This shows that digital transformation has a scale effect, and the larger the company, the easier it is to leverage a digital transformation. Enterprise digital transformation requires sufficient innovation and technological investments. Large companies are more capable of performing digital transformations and play a more significant role in promoting green development. However, small- and medium-sized companies are less innovative than large companies and less attractive to cutting-edge talent, resulting in a relatively slow digitalization process.

4.6.2. Heterogeneity Test Based on the External Macro Environment

As the external environment where the companies are located, this paper regressed construction companies according to their level of digital economy development grouped by the region in which they were located. This paper divided the provinces (regions and cities) where the companies were located for the group regression into provinces (regions and cities) with greater digital economy developments and provinces (regions and cities) with weaker digital economy developments due to the differences in the levels of digital economy development occurring in the provinces (regions and cities) to which the companies belonged. The regression results are presented in columns 5 and 6 in Table 10. The results show that construction companies are located in areas where the level of development of the digital economy is weaker in the provinces (autonomous regions and municipalities) that have a relatively higher impact. The reason why regions with a higher level of digital economy development have complete infrastructure construction, advanced production management technology, and abundant production factor endowment is probably because of the combined influence of multiple advantages, which results in a relatively low effect of green development efficiency improvement created by their digital transformation. As for the provinces (regions and cities) with weaker levels of digital economy development, there is considerable room for improvement in promoting digital development. As a result, the promotion created by the digital transformation of companies is relatively more significant.

4.7. Test of Mediation Effect

In this paper, a mediating effect model was used to empirically analyze the impact mechanism. Both the level of green innovation (GTI) and human capital structure (Laborstruct) of companies were selected as mediating variables, and this paper referred to the test of the mediating effect proposed by Wen [57], and constructed the following model:

$$GD_{i,t} = \alpha_0 + \alpha_1 DCG_{i,t} + \sum \alpha_n controls_{i,t} + Firm_i + year_t + \varepsilon_{i,t}\ , \tag{8}$$

$$M_{i,t} = \beta_0 + \beta_1 DCG_{i,t} + \sum \beta_n controls_{i,t} + Firm_i + year_t + \varepsilon_{i,t}\ , \tag{9}$$

$$GD_{i,t} = \gamma_0 + \gamma_1 DCG_{i,t} + \gamma_2 DCG_{i,t} + \sum \gamma_n controls_{i,t} + Firm_i + year_t + \varepsilon_{i,t}\ . \tag{10}$$

M represents the mediating variable. Digital transformation breaks down the barriers to information flow, enabling a timelier exchange of knowledge, information, and data resources between the innovation subjects. This promotes the improvement of the efficiency of green technology innovation, encourages the research and development of low-carbon technologies and clean energy, and improves the green development efficiency of companies. In order to test if digital transformation promotes green development through improving the level of green technology innovation, this paper used the logarithm of the green patent application volume of companies after adding 1 to represent the level of green technology innovation (GTI). It used this as the mediating variable for the regression analysis. The results are presented in columns 1, 2, and 3 in Table 11. It shows that the regression coefficient of green innovation is significantly positive at the 1% level. In addition, the bootstrap method (random sampling 2000 times) was used in this paper. The results are [0.0276, 0.1637], excluding 0, indicating that the mediating effect holds. Digital transformation is one of the paths for companies to achieve green development by enhancing green technology innovation. In order to further explore the mediating effect of different types of green innovation practices between digital transformation and green development, this paper divided green innovation into inventive green innovation (INGP), which is represented by the number of inventive green patent applications, and improved green innovation (NEWGP), which is represented by the number of utility green patent applications. Among them, green invention patents are breakthrough innovations in products or processes, which help companies achieve the goals of energy saving, emissions reduction, and improved production efficiency. Green utility patents focus on product enhancement or functional expansion without changing the technical principles of the original products. The results are shown in Table 12. In the digital transformation of green development, inventive green innovation has a more significant impact than improved green innovation. This results is mainly in agreement with the study conducted by Xiao [58].

Table 11. Mediation effect.

Variable Name	Mediation Effect					Moderating Effect
	GD	GTI	GD	Laborstruct	GD	GD
	1	2	3	4	5	6
DCG	0.4482 *** (4.99)	11.7793 *** (6.20)	0.8332 *** (6.28)	0.6484 ** (2.35)	0.4155 *** (4.64)	0.8332 *** (6.28)
GTI			0.0081 *** (3.36)			
Laborstruct					0.0504 *** (3.02)	
ER						0.0898 *** (4.47)
DCG × ER						1.0435 ** (2.04)
_cons	0.9762 *** (47.74)	0.5078 (1.17)	0.9720 *** (48.10)	0.4746 *** (7.55)	0.9522 *** (43.83)	3.0337 *** (5.14)
Controls	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	379	379	379	379	379	379
R^2	0.0995	0.1560	0.1261	0.0687	0.1211	0.3666
F test	5.86 ***	9.80 ***	6.67 ***	3.91 ***	6.37 ***	—
Bootstrap test		[0.0276, 0.1637]		[0.0026, 0.06279]		—

Note: T-statistics are shown in parentheses. *** and ** indicate 1% and 5%, respectively.

Table 12. Mediating effects of different types of green innovation.

Variable Name	GD	NEWGP	GD	INGP	GD
	1	2	3	4	5
DCG	0.4482 *** (4.99)	7.1105 *** (4.96)	0.0067 ** (2.06)	10.0819 *** (6.61)	0.0081 *** (2.68)
INGP					0.3663 *** (3.89)
NEWGP			0.4008 *** (4.34)		
_cons	0.9762 *** (47.74)	0.7320 ** (2.24)	0.9713 *** (47.39)	0.2922 (0.84)	0.9738 *** (47.97)
Controls	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Obs	379	379	379	379	379
R^2	0.0995	0.1176	0.1097	0.1715	0.1167
F test	5.86 ***	7.06 ***	5.70 ***	10.97 ***	6.11 ***
Bootstrap test		[0.0113, 0.1526]		[0.0142, 0.1497]	

Note: T-statistics are shown in parentheses. *** and ** indicate 1% and 5%, respectively.

In companies, the digital transformation process can optimize the human capital structure and improve the level of human capital. High-quality human capital has a more innovative capacity and higher labor productivity, which improves the pollution treatment capacity of companies. It can play a prominent role in economic growth and the green development of companies. The results are presented in Table 11. It shows that digital transformation promotes the green development of construction companies through the optimization of human capital structure. On the one hand, digital transformation has reduced the demand for low-end labor and increased the demand for R&D personnel and high-end talent in companies. It promotes integrating technology and knowledge into products and services, and drives efficiency improvements in companies. On the other hand, improving the high-end human resource allocation capacity of companies enables individuals with different levels of knowledge to communicate with and inspire each other. The knowledge spillover effect promotes collaborative innovations and the green development of construction companies.

4.8. Moderating Effect

To reveal the mechanism of the role of digital transformation and the green development of construction companies, this paper examined the moderating effect of regional environmental regulations. Equation (11) was established using the existing literature:

$$\mathrm{GD_{it}} = \eta_0 + \eta_1 \mathrm{DCG_{i,t}} + \eta_2 \mathrm{ER_{i,t}} + \eta_3 \mathrm{c\_DCG_{i,t}} \times \mathrm{c\_ER_{i,t}} + \eta_4 \mathrm{Controls_{i,t}} + \sum \mathrm{Firm} + \sum \mathrm{Year} + \varepsilon_{i,t}. \tag{11}$$

ER represents the intensity of environmental regulations in the region. In case of the multicollinearity caused by the interaction term, the independent and moderating variables were centralized for the interaction term. If η_1 and η_3 are both significant, this proves that the intensity of environmental regulations has a significant moderating effect on digital transformation and green development. On this basis, if η_1 and η_3 are the same sign, environmental regulation strengthens the impact of digital transformation on green development. On the contrary, it presents an inhibitory effect.

Part of the literature considers that policy pressure is the main driving force for green transformation and extracts a "government policy–enterprise action–enterprise performance" driving path [59]. The government forces green transformations by implementing environmental regulation policies and monitoring companies [60]. The implication of the institutional regulation theory is to standardize organizational behavior through economic and social regulations. As an important part of high-quality economic development, environmental regulatory policies inevitably affect enterprise green development. When companies face severe environmental regulation, they prefer to choose digital transformation technology to monitor the ecological changes occurring in the production process. Thus, it can effectively control pollution levels, reduce resource waste and pollutant emissions, and enhance the green development level of the construction industry [13]. At the same time, financial penalties, declining subsidies, and reputational damage associated with environmental regulations are scruples of companies. In order to investigate whether regional environmental regulation have any effect on the relationship between the digital transformation and green development of companies, this paper explored the moderating effect of environmental regulations. The regression results are presented in column 6 in Table 11. The results show that the estimated coefficient of DCG × ER passes the 5% significance test and the direction of the coefficient is consistent with that of DCG. Therefore, environmental regulation can strengthen the impact of digital transformation on the green development of construction companies. This result is consistent with Wang's results [61]. The reason for this is that, under the high intensity of environmental regulation, companies confront more severe losses, such as financial penalties and reduced financial subsidies. As a result, companies are more inclined towards digital transformations in response to policy requirements. Companies are boosting their competitiveness by enhancing their competitive advantages and enabling green transformations. Therefore, they realize the additional benefits of digital transformations while avoiding regulatory risks. In contrast, when the intensity of environmental regulations is weak, companies are less apprehensive of the regulatory risks and lose focus on green transformations, and thus lack the incentive to digitally transform themselves.

4.9. Threshold Effect

Environmental regulation not only have a moderating effect on the digital transformation that promotes green development in construction companies, but also with the intensity of environmental regulation, there may be a phase change in the digital transformation concerning green development. That is, there is a threshold characteristic. To verify this effect, this paper tested environmental regulation as a threshold variable to explore whether there is a difference in the impact of digital transformation on green development in different intervals. Drawing on Hansen's study, the following model is constructed [62]:

$$GD_{it} = \rho_0 + \rho_1 DCG_{i,\,t} * I(ER_{i,t} < \delta_1) + \rho_2 DCG_{i,\,t} * I(\delta_1 \leq ER_{i,t} \leq \delta_2) + \rho_3 DCG_{i,\,t} * I(\delta_3 < ER_{i,t}) + \sum \rho_k Control^k_{i,t} + \mu_i + \sigma_t + \varepsilon_{i,\,t}. \tag{12}$$

Before estimating the threshold model, a panel threshold existence test was conducted based on Hansen's panel regression method [62]. The results are estimated under overlapping simulated likelihood ratio test statistics of 500 times with a 95% confidence interval. The results show that environmental regulations pass the single and double threshold tests significantly, and the corresponding threshold effect test results and model estimation results can be observed in Table 13, respectively. Therefore, there is a double threshold for environmental regulations, which verifies H5.

Table 13. Significance test of the threshold effect.

er	Threshold	F Value	*p* Value	Bootstrap	1% Threshold Value	5% Threshold Value	10% Threshold Value	95% Confidence Interval
Single	0.2755 ***	23.51	0.0000	500	14.7194	10.0312	7.8675	[0.9778063, 1.59601]
Double	0.5645 **	22.77	0.0480	500	21.4824	12.3383	8.7448	[1.761382, 3.309598]
Triple		21.96	0.2320	500	44.7747	26.6857	20.0056	

Note: **, *** indicate that they passed the significance test at the level of 5%, 1%.

From the regression results of the threshold effect in Table 14, we can observe that when ER < 0.2755, it passes the 1% significance level test; however, the promotion effect is weaker. The most significant effect was observed when 0.2755 ≤ ER < 0.5645. However, the significance decreased when the threshold was below or passed the stipulated level. This proves that the effect of digital transformation on green development is significantly enhanced when environmental regulation is increased beyond the threshold level. However, when environmental regulation is too strong, it instead weakens the effect of digital transformation on green development.

Table 14. Threshold effect.

Variable Name	Environment Regulation Effect
	GD
	1
DCG (ER < 0.2755)	3.99 *** (0.5297)
DCG (0.2755 ≤ ER ≤ 0.5645)	8.19 *** (1.2870)
DCG (ER > 0.5645)	6.44 *** (2.5355)
Controls	YES
_cons	18.47 *** (0.7041)
R^2	0.3852

Note: T-statistics are shown in parentheses. *** indicate 1%.

5. Discussion

Using and empirical testing A-share-listed companies in Shanghai and Shenzhen as the research samples from 2015 to 2021, we present the following discussion.

Firstly, in order to measure the cost of digital transformation, this paper used textual analytics for the study. Moreover, the level of green development was examined by green total factor production. Then, empirical research was conducted to determine how digital transformation affects green development in construction companies. After testing benchmark regressions and several reliable endogeneities, the results still support the idea that digital transformation has a positive impact on green development in construction companies. This result is consistent with those obtained by Wang and Gao, who studied macro-perspective [63,64]. At present, limited by the complexity, uncertainty, and fragmentation of the construction process characteristics, the construction industry is still in a state of extensive development in China. Problems, such as poor production methods, low labor efficiency, and high consumption of energy and resources, are still prominent. At the same time, there is also the presence of inadequate industrialization and informatization in the construction industry, lacking scientific and technological innovation capabilities, which urgently require the implementation of structural changes in the development of the construction industry. Science and technology innovation development concepts, the new stage of scientific and technological revolutions in the context of digital technology to achieve scientific and technological innovations in the construction industry, the transformation of production methods, and industrial structure adjustments and optimizations drive the green development and transformation and upgrading of construction companies. Indeed, digital transformation enables companies to effectively integrate the concept of sustainability into their digital strategies [65]. The use of digital technologies also helps companies to monitor energy inputs and manage resources, thereby reducing energy consumption and pollution emissions on the production side [66].

Secondly, companies create significant positive effects on digital transformation for the green development of construction companies by improving green innovation and optimizing human capital structure. In particular, digital technologies can help companies link technology, data, and knowledge chains, providing favorable conditions for green innovation [67]. This result is in alignment with He's results [68]. The sustained momentum of green innovation effectively solves more complex environmental and technical problems, and thus promotes the green development of companies. At the same time, digital transformation improves green development by solving more complex environmental and technical problems. In addition, the intensity of the permeability of digital transformation accelerates the speed of knowledge innovation and knowledge spillover, activates enterprise green innovation kinetic energy, promotes green technological innovation, and expands the green development of construction companies [69]. Digital transformation and green technology are combined to activate the potential of digital elements and realize the green development of construction companies. With the application of enterprise digital technology in intelligent production and research and development scenarios, the extensive use of enterprise informatization and digital technology will increase the demand for high-education and high-skilled workers and have a crowding-out effect on low-education and low-skilled labor outcomes. Indeed, the combination of data elements and human capital is beneficial to increase the knowledge and technology content of companies, which in turn stimulates green development. In addition, the digital transformation of construction companies has a higher demand for talented individuals, who have more knowledge reserves, are more resilient and are more capable of conducting innovative activities, which have a more pronounced impact on the level of green development of companies. This conclusion is in line with Zhou's results [70].

Thirdly, we observed that environmental regulation enhanced the environmental awareness of firms, promoted the strengthening of green technological innovation in digital transformation, and promoted the green development of construction firms. This result is consistent with Yang's results [71]. With the successive introduction of various environmental regulations, companies are facing increasing pressure. Under the "dual-carbon" goal, the government has adopted long-term governance tools and regulatory agencies to regulate and fine companies. These pressures will drive companies to engage with environmental management and green innovation practices more substantially. This has also prompted companies in regions with stronger environmental regulations to be more inclined to invest more money in energy saving and emission reduction plans and other related digital transformation technologies to reduce pollution emissions and promote the green development of enterprises. Moreover, through the threshold test, we observed that environmental regulations worked best in the appropriate band. Below or above this threshold, they played a relatively minor role, resulting in a limited number of incentives for companies to reduce their emissions.

Fourthly, we discovered that both the internal features and the external environment might have influenced the effect of implementing digital transformation, which promoted green development in companies. In the first place, on the one hand, according to the characters of the companies, the impact of the digital transformation of state-owned companies on green development would be more significant. The argument was that state-owned companies have the edge over non-state-owned companies in terms of policy systems, capital propensity, and extensive external financing channels. So, state-owned companies are capable of gaining access to more plentiful innovation resources and recruiting more highly educated individuals [72]. On the other hand, digital transformation requires the large-scale application of digital technologies, such as big data, artificial intelligence, and the Internet, which requires constructing modern information systems and large-scale investments. Since state-owned companies have more advantages in terms of capital and scale, they are more effective in the digital transformation process for green development. In the second place, according to the size of companies, digital transformation significantly impacts green development in large companies. This is because large companies have better reputations and capital absorption capacities than small- and medium-sized companies, greater substantial R&D capability, and better professional and technical personnel. In contrast, SMEs are less efficient in digital transformation; the quality is worse than large companies, and the digitalization process is relatively slow. As a result, the effect of large companies is more evident. This conclusion of the study is in line with Zhang's results [73]. Last, but not least, according to the external environment of the region in which the enterprise is located, the weaker development of the digital economy in the region, the construction enterprise's digital transformation to promote the green development of the enterprise has a more significant impact. Regarding the better development of the digital economy, companies have fully recognized the advantages of the uses of digital technology and mining to disseminate information in the field of green governance. In areas with weaker digital economy developments, companies can show the government their strengths and information through their roles in digital transformation. This will help them break the constraints placed on pollution control created by the growth of the digital economy and promote green development. Therefore, the positive effect of the digital transformation of construction companies on green development can be better reflected in regions with a weaker digital economy. Therefore, in construction companies, the positive effect of digital transformation on green development can be better reflected in regions with a weaker digital economy.

6. Conclusions

According to the discussion, this paper determined the following research conclusions. (1) The digital transformation of construction companies improves green development. Additionally, the benchmark regression results are significant at the 1% level. (2) The promotion effect of the digital transformation of construction companies on green development is more prominent in state-owned, large companies, and located in a weaker level of development of the digital economy. (3) Green technological innovation and human capital structure are the mediating variables in promoting green development through the digital transformation of construction companies. (4) The level of environmental regulation plays a positive moderating effect. (5) There is a double threshold effect on environmental regulation, and when $0.2755 \leq ER \leq 0.5645$, the digital transformation of construction companies promotes green development most conspicuously.

The limitations of this paper and future research perspectives are reflected in the following areas. Firstly, the conclusions determined from exploring the listed construction companies also apply to non-listed and small-sized companies. For example, such companies should increase their awareness of digital transformation. They should pay attention to the cultivation of technically skilled individuals and actively cooperate with universities to ensure a supply of talent. Additionally, they should increase the level of technology and promote the green development of companies. Therefore, non-listed or small construction companies can be used as the research sample for an in-depth exploration in future research. Secondly, the limited amount of data that can be collected means that, in future research, more data obtained from construction firms can be used as research samples to explore the possible differences in the adoption and effectiveness of digital transformations in different construction companies. Thirdly, this paper only examined the impact of environmental regulations, digital economy strengths, and weaknesses on the digital transformation of construction firms to improve green development. However, in fact, there are more external factors that can affect this relationship, which deserve further exploration, such as market demand and social awareness. In future research, other external factors can be screened as control variables to be added to the benchmark regression for exploration.

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