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Can Digital Transformation Drive Green Transformation in Manufacturing Companies?—Based on Socio-Technical Systems Theory Perspective

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Abstract: The current world's green economy and digital economy collide at an accelerated pace, and the deep integration of digitalization and greening has become a new requirement for high-quality industrial transformation. Premised on a socio-technical system (STS)'s theoretical viewpoint from Chinese manufacturing firms, the study examines the effects of the digital transformation (DT) of companies on green transformation (GT), as well as the function of channels and processes. This study uses 70 samples of A-share-listed Chinese manufacturing companies from 2013 to 2020; a combination of linear regression and fsQCA is used to empirically test the research model and analyze the equivalence path. It is found that (1) DT significantly drives the GT of manufacturing firms; (2) DT influences the GT of manufacturing firms by alleviating the information asymmetry problem; and (3) executive team heterogeneity plays a positive mechanism role in the relationship between DT and GT. The qualitative comparative analysis yields two types of paths: (1) the main constructs that shape high GT levels are high DT intensity, low information asymmetry, and high TMT gender heterogeneity, which mainly arise in the eastern region and play a more pronounced role in state-owned enterprises, heavy pollution, and high-tech industries; (2) for non-state-owned enterprises in traditional industries in the central and western regions with average digital development, high TMT gender heterogeneity is the key to GT. The study expands the application of related theories and has practical implications for how Chinese manufacturing enterprises can effectively promote GT.

Keywords: Chinese manufacturing companies; digital transformation; green transformation; information asymmetry; top management team heterogeneity (TMT heterogeneity); fuzzy set qualitative comparative analysis (fsQCA); socio-technical systems theory (STS)

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1. Introduction

China's economy has improved significantly since the reform and opening up, but the resulting issues with high energy consumption, high emissions, and high pollution are progressively posing challenges to sustainable development. The manufacturing industry is the pillar and engine of China's economic development, but it is also the main area of energy consumption, environmental pollution, and carbon emission. Green transformation (GT) involves the "greening" of the whole cycle so that manufacturing enterprises can be resource-saving and environment-friendly; focus on resource conservation, emission reduction, and efficiency improvement; and pursue the harmonization of environmental and economic benefits [1], which has been listed as an important national policy in China and is also a hot issue for scholars. However, the transformation faces multiple challenges such as institutional and institutional barriers, awareness barriers, technological barriers, and resource barriers leading to the lack of motivation and slow process of enterprises [2], and the manufacturing industry urgently needs to break the dilemma and usher in a new life.

With the continuous emergence of digital technologies represented by "ABCDI" (artificial intelligence, blockchain, cloud computing, big data, and the Internet of Things) technologies, digitization is becoming a key stroke to reshape the way enterprises develop [3]. Most recently, China's digital economy has flourished and the pace of digital transformation (DT) of enterprises has accelerated, such as the application of smart manufacturing, Internet business models, and modern information systems, which can not only empower traditional industrial chains with data in all aspects but also give rise to new industries and new models through cross-border integration, further enhancing the competitiveness of the industry [4]. Given that the digital economy has shown great transformative power in integrating with traditional industries, the impact of digital development on the green behavior of enterprises has also become a topic of keen interest for scholars, for example, Zhou [5] pointed out that digital network smart manufacturing can improve the quality of the products, performance, and services of enterprises and reduce resource consumption; Belhadi [6] identified the direct positive impact of big data on environmental performance from the perspective of a resource-based view; Ai [7] found through an empirical study that regional big data development can promote corporate green innovation; Xiong [8] researchers used 430 heavy metal companies in the Yangtze River's middle reaches as a research sample, and they discovered strong spatial correlations between DT and pollution control. The research ideas and empirical approaches in the existing literature provide valuable empirical lessons and insights for understanding digitalization as a driver of green development in the Chinese context. As is evident, the majority of the research now in circulation examines how digital development affects green innovation, consumption, and emission reduction aspects, but does not address how the DT of firms goes green and its transmission mechanism.

As a micro-particle of the economy and society, the digital development of the wide area will eventually be internalized into the DT of enterprises. Studying the effects of the DT of businesses on the GT is extremely important from both a theoretical and practical standpoint given the present need to accelerate the GT of the development mode. However, at present, such studies are still very insufficient and lack the support of rigorous empirical tests and management theories.

Under different boundary conditions, the impact of DT on enterprise consumption and emissions reduction may yield heterogeneous or opposed findings [8]; therefore, another key to the research is how and under what conditions DT affects the occurrence of GT. Socio-technical system (STS) theory, as an interdisciplinary and integrated framework, provides a unique perspective for analyzing the impact of new communication technologies [9]. It distinguishes organizations into technological and social systems and emphasizes that technological systems lead to the progress of social systems. Technological systems are often defined as "the network of technologies, equipment, and knowledge that an organization acquires, utilizes, and exports", while social systems are considered "the way people in an organization interact with the outside world" [10], and both of them work together through the coordination role of managers. The two affect the behavior and performance of the firm through the coordination of managers [11]. The significance of STS theory in researching the Internet of Things and artificial intelligence has been shown in existing studies [9], and green supply chain management [10], pointing out that the use of digital technology has revolutionized technological systems, which in turn have contributed to the advancement of social systems in their interactions with people, leading to improved organizational performance. However, the application of STS theory to the DT and GT of enterprises has been rarely explored, and there is a lack of profound exploration of the interactions between factors under this theory. Therefore, based on the socio-technical systems theory, this paper attempts to explore the channel role and mechanism role of information asymmetry and TMT heterogeneity on the effect of enterprise DT on GT from the viewpoint of inter-system information transmission and relationship regulation.

Founded on the above contextual information, this paper uses a sample of Chinese A-share-listed manufacturing firms from 2013 to 2020 to examine the green empowerment of DT from the perspective of socio-technical systems theory. The possible marginal contributions of this study are as follows: (1) compared to existing studies, this paper focuses on the impact of DT on GT at the micro level of manufacturing firms, using information asymmetry and TMT heterogeneity as channels and mechanisms to supplement research on data empowerment and green development; (2) the digital economy not only brings a great impact on production practices but also brings explanatory power to traditional organization theory challenges. This paper introduces the STS theoretical analysis framework into the study of digitalization and the GT of manufacturing enterprises, which extends the application scope and theoretical scenarios of the theory; (3) in terms of research methods, a regression analysis and fsQCA are combined, which not only overcome the limitation of a regression analysis based on the one-way linear relationship to a certain extent [12], but also make up for the defect that fsQCA cannot analyze dynamic panel data, making the research results more convincing and realistic, which is a useful attempt to combine qualitative and quantitative methods; (4) compared with a linear analysis that mostly focuses on the net effect between variables, this study emphasizes the consideration of multiple potential concurrent causal relationships on the basis of correlation [12], which is useful for how manufacturing enterprises in different industries, ownership, and regions allocate data resources, information resources, and executive resources to promote a high level of GT to occur as a guiding role.

2. Literature Review and Hypothesis Development

2.1. The Meaning and Impact of DT

The discussion on the meaning of DT has not yet formed a unanimous opinion, and most scholars currently agree with the "trilogy theory" proposed by Verhoef [3]: the DT of enterprises is composed of digitization, digitalization, and digital transformation. The first two phases are incremental processes of digital transformation, described as digitizing existing business processes through coding [13] and using digital technologies to add value to them [14]. In the last phase, the business model of the company is strategically changed, which creates more value for the company. Further, the DT of manufacturing enterprises has also received keen attention from scholars, and Zhou argues that manufacturing enterprises will go through a three-stage transformation process of digitalization, networking, and intelligence after deep integration with digital technologies [5]. This will reshape the whole life cycle of products; enhance the customer experience [11]; and promote the emergence of new technologies, products, and services, which are the main driving forces for the transformation and upgrading of manufacturing enterprises. Founded on the previous research, this paper divides the concept of the DT of manufacturing enterprises into two stages: (1) digital technology forms an initial penetration effect inside and outside the organization to improve the operational efficiency of enterprises and optimize the value-creation process; (2) digital technology forms a deep integration effect with enterprises to transform the competitive business model and business model, data empowerment for each link, and the establishment of a digital competitive advantage.

The impact effects of DT as an emerging strategic choice for firms have become a hot topic. Firstly, from the perspective of operational development, DT significantly improves firms' operational efficiency, organizational performance [15], innovation level [16], and stock liquidity level [17], which in turn increases participant satisfaction and capital market activity. Secondly, from the perspective of transformation and upgrading, DT makes the boundaries of firms blurred, making it easier to engage in cross-border disruptive and open innovation, expand the added value of products and services [18], and reconfigure business processes and value chains [15]. It has also been pointed out that due to the lag between DT and business performance and the high costs associated with the long-term nature of the transformation, only some companies obtain the expected revenue growth from DT, resulting in the "digital paradox" phenomenon [14,19]. The variability of results in existing studies suggests that the specific mechanisms and scenarios of DT need to be further explored.

2.2. Influencing Factors of GT

With the growing awareness of sustainable development, industries are continuously using green means to improve their production and operation methods in order to seek the synergistic development of the environment, society, and economy [20]. As a key link of sustainable development, GT in the manufacturing industry represents a scientific development model of low carbon, consumption reduction, and emission reduction in the whole life process from initial R&D and production to final product recycling and decomposition [21], and its influencing factors have been the focus of scholars' attention [2].

From the external perspective of environmental analysis, and with government involvement as a characteristic of China's market economy, the government's regulatory behavior becomes a strong motivation and pressure source for the green transformation of Chinese manufacturing enterprises [22]. In terms of regulation, pressure-based environmental policies such as environmental regulations [23,24], environmental information disclosure [25,26], and environmental taxes [27] can effectively guide enterprises' green behavior, raise their awareness of environmental protection, and promote the research and development of low-carbon emission reduction technologies [21]. In terms of incentives, the government alleviates the environmental pressure from regulation by implementing green subsidies [28] and energy-saving consumption incentives [29], etc., making it more likely for firms to explore GT practices. Moreover, compared with other measures, incentive tools present superior economic efficiency in addressing environmental externalities [30]. In addition, the bootstrapped lack of incentive policies such as industrial policies [31], green credit policies [32], and carbon emissions trading policies [33] can complement the above environmental policies and accelerate the realization of corporate GT through a combination of policy instruments. In addition to policies, public attention, public pressure, and consumer propensity to buy green are also important factors that pull firms to GT. Public pressure [34] and consumer intention [35] prompt enterprises to develop environmental strategies [36] and engage in self-restraint of environmental behavior, which can enhance the sustainable development performance of enterprises. GT requires stable and large sources of capital, and endogenous financing is difficult to meet the demand, so the development of green finance will help to stimulate the vitality of enterprises and promote the development of new green projects [37].

From the internal perspective of the environmental analysis, dynamic capabilities and innovation literacy within the organization are also important factors integral to GT [2]. Technological innovation is an exogenous variable of corporate GT, which increases the added value of manufacturing companies through the accumulation and overlay of knowledge toward technology-intensive and clean industries [21,38]. In addition to this, executives with environmental intentions and environmental experience can promote active environmentally friendly projects internally and facilitate the exchange of information on environmental strategies across organizational boundaries externally [39], with a greater propensity to make green investments [40] and guide environmental practices. This type of green transformational leadership can create a positive environmental climate within the company, which in turn can inspire pro-environmental behavior among employees [41] and help the company achieve higher environmental goals.

In addition, scholars have explored ESG ratings [42] and green M&A [43], which have improved the study of the influencing factors of GT from various aspects and also provided references and ideas for the study of this paper.

2.3. DT and GT

Under the wave of the "fourth industrial revolution", the growth of GT in manufacturing enterprises is being influenced by DT more and more. Most of the existing studies on digitalization for green development focus on economic value, such as Dyatlov [44], who points out that DT can promote green innovation among interregional enterprises through integration and synergy; Wen [45], who takes Chinese manufacturing enterprises as a sample, reveals that the process of industrial DT greatly improves the environmental performance of businesses; further researchers have elaborated on the effects of DT on production efficiency, green supplier networks, and green financing [4,8,46]. However, the value of DT should be reflected not only in the financial performance but also in non-economic values such as environmental value [2,44]. Based on this, the following section will explore the environmental value of DT from the perspective of GT.

From the R&D and production side, digitalization brings new changes in processes, decision-making, and technology for manufacturing enterprises, which become the basis for GT. First, DT adds existing manufacturing practices with digital capabilities, which can optimize and reorganize design and development, process flow, and resource utilization; realize fine management of the whole product life cycle; shrink R&D cycles and production costs; and contribute to lean synergy effects [45], thus realizing green and intelligent production. Secondly, digitally transformed enterprises can realize the tracking of data of the whole production process and monitor environmental changes in real-time, which is conducive to controlling pollution sources [47] and improving the environmental performance of enterprises. Third, the construction of digital platforms provides a convenient communication channel for both supply and demand, and enterprises can receive a large amount of real-time information "without leaving home" so that the production mode moves from "manager-centered" to "customer-centered". This will effectively meet the personalized demands of consumers, enable enterprises to precisely reduce the scale of production [48], reduce the waste of resources caused by "invalid inventory", and ultimately reduce the uncertainty of GT and empower the GT of R&D and production.

From the sales and service side, DT brings new changes to the marketing model, business model, and service model for manufacturing enterprises, and pulls the GT of enterprises by promoting green development on the demand side. The high volatility and uncertainty of the green market have been the pain point of the difficult and slow transformation of enterprises. Dynamic capability theory states that the ability to perceive, capture, and transform demand in the face of a volatile environment is the key for organizations to gain a competitive advantage [49]. By collecting consumers' browsing preferences, behavioral patterns, and transactional data related to green products, and using digital technologies for social-emotional analysis and natural language processing, companies identify their green needs and provide selected content to potential customers to increase the chances of purchasing green products [50]; digital seizure capabilities enable companies to make effective response decisions after perceiving green needs, such as dynamic real-time pricing and predicting competitors' strategies, etc. [51]; based on perception and seizure, companies further use data for cash flow, supply model, and financial risk planning to improve operational systems and management efficiency [50], helping GT to occur. In addition, the construction of a modern intelligent service platform based on digital technology has enabled traditional manufacturing companies to shift from a single offline provision of products and services to an online model, with a reduction in resource consumption and pollution emissions from physical activities. The digitization of the service side enables enterprises to provide targeted consultation and services to customers and develop towards intelligence, initiative, and personalization, enhancing the green image of enterprises and further adding to the GT.

As a comprehensive analysis of the above, this paper puts forward the following hypothesis:

H1. *DT of manufacturing enterprises can promote their GT.*

2.4. The Role of Channels of Information Asymmetry

Information asymmetry refers to the inequality or incompleteness of information between parties to a transaction, which has an impact on trading behavior and market efficiency, generating problems such as adverse selection and moral hazard [52]. Since Stiglitz's [53] study on credit rationing, research on information asymmetry has been focused on finance and the financial industry, affirming the positive effect of reducing information asymmetry on improving transaction efficiency and reducing transaction costs. Combined with the background of the integration and development of digitalization and greening, research on information economics argues that, on the one hand, digital technology penetrates the whole process of information collection, transmission, analysis, and application, which expands the sources of information, enhances the information analysis ability, and reduces information asymmetry [54]; on the other hand, the improvement of information asymmetry can reduce the cost of green production and transaction, improve the return of green products, and optimize resource allocation, thus motivating enterprises to make GT [55]. It can be inferred that information asymmetry may be the key channel through which DT affects GT.

STS theory suggests that information elements determine how technical and social systems interact [52]. The enterprise, as an STS, is composed of four elements—technology, task, participants, and organization—in a coordinated manner, and is characterized by dynamic interaction, diversity, and variability [56]. This determines that the GT relies on the transformation of technological systems as well as the challenge of interacting with social systems [57]. Digital intelligence manufacturing brought by DT innovates the technological system of manufacturing enterprises, and at the same time, the technological system becomes the medium of interaction between the organization and the environment by optimizing the pathway of information transmission and reducing the information asymmetry between and within systems [10], which in turn lead to the effective integration and collaboration of complex elements in the social system and can enhance the green value and green performance of the organization, improve the resistance to market risks and identify green opportunities, and influence the occurrence of GT. Based on this, regarding the classification basis by Wu [57], the channel role of DT in advancing corporate GT by alleviating information asymmetry is elaborated at a total of four levels from the technology and tasks of the technological subsystem, and organizations and participants of the social subsystem.

1. In the GT context, the technological dimension mainly refers to the cultivation and formation of green technologies. Digitally transformed manufacturing enterprises have more complete digital systems compared with traditional enterprises, which accelerate the delivery and feedback of information within the organization, and the real-time sharing of data can enable enterprises to have higher production flexibility and supply chain synergy [58], which promote the combined innovation of green technologies; meanwhile, linear or non-linear interactions occur between various types of old and new technologies, which generate the amplification effect of innovation [59] and can provide a low-cost and efficient way to innovate green technologies. Organizations can also obtain a large amount of external green information and knowledge through information networks, and obtain the spillover effect of green technology innovation [60], which effectively promotes the occurrence of GT.
2. The task level refers to the impact of environmental policies. From the existing studies, weak regulation, inappropriate policies, and resource misallocation are the main reasons that prevent the "government hand" from playing a regulatory role [7]. On the one hand, the government, as a weak party with information asymmetry, has difficulty in distinguishing the authenticity of companies' environmental information, which hinders policy formulation and effective monitoring. On the other hand, companies may engage in rent-seeking behaviors, such as "strategic innovation" [61], to obtain financial support, resulting in resource mismatch. In the face of these problems, DT is considered to be the key to effectively alleviating the information asymmetry between the government and enterprises and promoting the GT of enterprises. For the government, DT makes the environmental data of the whole process of enterprise value creation traceable; breaks the information barriers led by enterprises; and provides a targeted and dynamic basis for policy formulation, subsidy issuance, supervision, and inspection. For enterprises, digitalization enables the government to improve the level of regulation and the state of resource allocation, which will, to a certain extent, inhibit speculative behavior and enhance the confidence and determination of enterprises in GT; at the same time, according to the signal theory [54], enterprises

that receive government support can send positive signals to all parties, enhance the investment confidence of social capital, and guide the aggregation of production factors, which will, in turn, promote GT.

3. The organizational level mainly refers to the digitization of management. Digitalization has changed the management process of enterprises, blurred organizational boundaries, broken the information silos between departments and organizations by integrating the resources of all parties, and redefined the competition model and business management style [62]. At the same time, DT flattens the organizational structure and can reduce the decision and action errors caused by information loss. For managers, sifting through unorganized masses of data becomes easy, and they use digital systems (e.g., DM, DSS) to discover connections between things and reduce the dependence on experience and intuition when making decisions. Moreover, digitalization improves the process of the revision, implementation, monitoring, and feedback of internal control systems, and changes organizational structures, helps managers to identify problems promptly [54,63], and enhances the resilience of organizations in the face of green risks.
4. An important aspect at the participant level is the green shift at the consumption end. The unique double externality of GT makes it difficult for enterprises to benefit in the short term, resulting in insufficient motivation and slow progress. Therefore, the GT on the demand side is particularly important in terms of forcing and guiding the GT on the supply side [29]. In the Chinese context, an insufficient effective supply of green products and weak awareness of green consumption are the main issues that affect the driving effect [64]. The reason is that enterprises do not understand consumer demand well enough, which makes it difficult to translate the value of green output in the market. DT provides an opportunity to promote the linkage of information between supply and demand. First of all, when enterprises have a high level of digitalization, they can use the "data power" to form a "co-evolution" mechanism with customers [7] to realize the analysis of massive information, the prediction of demand direction, and the guidance of consumption tendency, and to realize the value of green products. The second point is that enterprises can use various information channels to improve their competitive position in the market. Furthermore, enterprises can "push" the demand subjects through various information channels [54], so that stakeholders can grasp more information about the green management of enterprises and enhance the positive concern and environmental expectations of the outside world, thus establishing a green and responsible image of enterprises and enhancing the sustainability of the GT of enterprises.

By synthesizing the above analysis, this paper proposes the following hypothesis.

H2. *DT of manufacturing enterprises indirectly promotes their GT by alleviating the information asymmetry problem.*

2.5. Mechanistic Role of TMT Heterogeneity

The top management team (TMT) originated from the higher-order theory proposed by Hambrick and Mason, which argues that the characteristics and attributes of the TMT, i.e., TMT heterogeneity, determine the strategic choices and performance levels of corporate development [65]. Currently, the digital economy is developing rapidly and DT is seen as an opportunity to improve corporate productivity and environmental performance [66], and the TMT, as the core of corporate leadership, holds organizational resources such as financial, information, technological, and physical resources [67] and determines the decision-making and action execution [68], which require it to seize the opportunities of digitalization and shoulder the responsibility of identifying the strategic potential of DT and responsibility in allocating resources [69] and reducing GT risks. In studies involving DT and GT, TMT heterogeneity has shown direct as well as indirect effects on digital and GT in different research contexts in terms of dimensions such as age, gender, educational status, functional background, and overseas background, respectively [66]. Thus, TMT heterogeneity may play a mechanistic role between DT and GT in manufacturing firms.

STS theory suggests that technological factors are always combined with human factors, where managers play an important role in the interaction between technological and social systems, driving the harmonization of both systems [70]. Under the undertone of green development, TMT can mobilize its organizational resources to integrate with the digital system of the enterprise and promote the efficient adoption of digital technology in GT [71]. At the same time, TMT heterogeneity can also have a potential differential impact on the environmental performance of firms [66]. Therefore, in this paper, based on previous studies and the availability of data, we describe the mechanisms of TMT heterogeneity in the following three aspects.

1. Gender heterogeneity. Green transition is seen as a balance between profitability and environmental protection and requires the moral courage of managers to make decisions [68]. Ecofeminist theory states that there is a strong relationship between feminine characteristics and nature, while men are more connected to culture. In other words, due to feminine characteristics, women are more environmentally conscious than men, which is reflected in organizations where gender diversity in the board of directors contributes more significantly to corporate green development and environmental performance [72]. In addition, the DT of a company can bring more decision-making power to female executives [66], and then female executives will be more sensitive to driving the DT of the company as well as the GT.
2. Education heterogeneity. Executives with different educational backgrounds hold differing strategic views and values, which influence the direction of change and the rate of growth. The challenging and risky nature of GT requires the risk tolerance and confidence of executives [68]. Better-educated executives have a high learning ability and tend to possess cutting-edge scientific knowledge and advanced management experience, and can quickly gain insight into social and market developments, adjust the direction of corporate development and innovate business models on time, and therefore pay more attention to the benefits of DT [66]. In terms of viewing the relationship between people and nature, the higher the level of education of the managers, the more their ethics and environmental awareness will prompt them to care about the impact of business operations on the environment and tend to choose sustainable development strategies [73].
3. Functional heterogeneity. TMT members may have diverse functional backgrounds, such as finance, marketing, administration, etc. The differences in specialization enable managers to have multiple views on problem entry angles and solution channels, which facilitate the company to make high-quality decisions based on multiple information resources. The differences in functional backgrounds are directly related to the accumulation of managers' experience, and the differences in practical experience can make managers differ in their sensitivity to opportunities and risks [67]. In today's rapidly evolving world of big data, TMTs with diverse functional backgrounds may lead companies to better seize the multi-level opportunities of GT and address complex challenges.

Synthesizing the above analysis, this paper proposes the following hypotheses.

H3. *TMT heterogeneity plays a positive mechanism role in the process of the DT of manufacturing enterprises to promote GT.*

H3a. *TMT gender heterogeneity plays a positive mechanism role in the process of the DT of manufacturing enterprises to promote GT.*

H3b. *TMT education heterogeneity plays a positive mechanism role in the process of the DT driving GT in manufacturing enterprises.*

H3c. *TMT functional heterogeneity plays a positive mechanism role in the process of the DT driving GT in manufacturing enterprises.*

3. Research Design and Data Description

3.1. Sample Selection and Data Sources

In this study, the listed manufacturing enterprises in Shanghai and Shenzhen A-shares from 2013 to 2020 were selected as the sample and processed according to Lei et al. [29] as follows: (1) enterprises in the manufacturing category were retained based on the Industrial classification for national economic activities; (2) enterprises with an abnormal status such as ST, *ST, and terminated listing were excluded; (3) enterprises with missing data and important indicators (such as fixed assets, number of employees, etc.) were excluded; (4) samples with less than 5 years of continuous data were excluded; (5) to reduce the impact caused by extreme and abnormal values, this paper has subjected the main variables to 1% and 99% tailoring.

The main sources of data in the article are as follows: (1) data on corporate GT were mainly obtained from the Juchao Information Network and corporate annual reports, environmental reports, sustainability reports, and social responsibility reports, which were collected and compiled by the author manually; (2) data on corporate DT, information asymmetry, and control variables were obtained from the CSMAR database. All outliers and repeated values in the sample data were manually corrected according to the official reports, and data processing and analysis were conducted using Stata16 software.

3.2. Variable Settings and Measurements

3.2.1. Explained Variable

Green Transformation (*GTFP*). Drawing on the analysis of the intrinsic mechanism of GT by Lei et al. [29], in this paper, the green efficiency (*GTFP*) is used as an indicator to measure the GT of enterprises by using the super-efficient SBM-DEA model based on non-desired output (non-oriented) and the Malmquist–Luenberger index (ML index for short) for measurement. According to the calculation principle of the ML index, each enterprise is treated as an independent production decision unit (DMU) for the construction of the annual production boundary, and after obtaining the ML index of each enterprise for each year, it is assumed that the value of a DMU is 1 in 2013, and the green efficiency of each period from 2014 to 2020 is obtained by multiplying the ML index of the current period with the ML index of the previous year, respectively [74].

The input–output indicators used for the measurement are as follows: (1) Referring to Wang [75] and Chen and Li [74], the number of employees is used as the labor input, the book value of fixed assets is used as the capital input, and the energy consumption of the enterprise is used as the energy input. Among them, the energy input is converted into standard coal for the data according to the General rules for the calculation of the comprehensive energy consumption. (2) The expected output is measured by the gross industrial output value of enterprises, and for enterprises that do not disclose this item in the social responsibility report, it is calculated as the sum of the main business income and the ending book value of inventory goods according to the accounting method of the National Bureau of Statistics. (3) For non-expected output, this paper manually collates the pollution emissions (each exhaust gas and wastewater emissions, such as sulfur dioxide, chemical oxygen demand, etc.) disclosed in all reports of enterprises and accounts for them by converting the relevant items in the Table of taxable pollutants and equivalent values in the Regulation on the Implementation of the Environmental Protection Tax Law of the People's Republic of China into pollution equivalents.

3.2.2. Explanatory Variable

Digital Transformation (*DT*). According to the connotation dimension defined in the previous section, the intensity of the DT of enterprises is divided into two dimensions: "technology penetration" and "digital application". Among them, "technology penetration" is the application of the five digital technologies of "ABCDI"; "digital application" is the paradigm shift brought by the application of digital technologies, such as industrial Internet, digital marketing, digital marketing, etc. In this paper, based on the word classification compiled by Wu [17], we refer to the latest DT-related literature and the 2021 White Paper on Big Data, White Paper on Trusted Artificial Intelligence, White Paper on Blockchain, White Paper on Cloud Computing, and White Paper on Digital Carbon Neutrality issued by the China Academy of Information and Communication Technology (CAICT), and expand the pool of DT words based on the characteristics of manufacturing enterprises' keyword pools, such as data exploitation, privacy computing, cloud data, cloud-native and cloud deployment at the technology penetration level, and 3D printing, smart terminals, and smart energy at the digital application level. The above characteristic words in the report are captured by Python software, and the final data of the two indicators are obtained by summing up the frequency counts of matching keywords.

3.2.3. Channel Role Variable

Information Asymmetry (*IA*). The financial data of the listed companies in CSMAR are chosen as the data source. Drawing on the study of Hutton [76], the absolute value of manipulable accrued profits calculated based on the modified Jones model is used to measure, and the higher the value, the higher the degree of information asymmetry of manufacturing firms.

3.2.4. Mechanistic Role Variable

TMT heterogeneity, including gender heterogeneity (*TMTG*), education heterogeneity (*TMTE*), and functional heterogeneity (*TMTF*) is explored. The director and supervisor's personal characteristics document in CSMAR is selected as the data source. Among them, the measurement of TMTG gender heterogeneity and educational heterogeneity is borrowed from Chen et al. [66] and is measured based on the proportion of female members in TMT, and the proportion of members with master's degrees or above, respectively; the measurement of functional heterogeneity is borrowed from Deng [77] and is measured using the Blau index (Herfindal–Hirschman index). The calculation formula is:

$$H = 1 - \sum_{i=1}^{n} p_i^2 \tag{1}$$

In the above equation, p_i refers to the proportion of members of category i in the TMT, and n represents the type of functional background (10 categories according to CSMAR's classification criteria). H takes a value between 0 and 1, and the closer to 1, the higher the heterogeneity of the functional background.

3.2.5. Control Variables

To attenuate the influence of other factors on the empirical results, the following control variables are introduced concerning the relevant literature on GT research at home and abroad: firm size (*Size*), years of listing (*Age*), level of financial leverage (*LEV*), nature of ownership (*SOE*), profitability (*ROTA*), and ownership concentration (*S-D*).

The main variables and their definitions are shown in Table 1.

3.3. Main Model Setting

To examine the impact of *DT* on the GT of manufacturing firms, the following regression model is constructed in this paper:

$$GTFP_{i,t} = \beta_0 + \beta DT_{i,t} + \sum \eta Controls_{i,t} + \varepsilon_{i,t} \tag{2}$$

where *GTFP* represents the level of the GT of enterprises, *DT* represents the intensity of the *DT* of enterprises, *Controls* is the set of control variables, and ε is the random disturbance term. If the parameter $\beta > 0$, it means that *DT* can promote the GT of enterprises.

Table 1. Main variables and definitions.

Variables	Definition
Green transformation	Green efficiency (*GTFP*) is used as a measure.
Digital transformation	*DT*, the keyword frequency is obtained by summing up the keywords at the level of technology penetration and digital application, respectively.
Information asymmetry	*IA*, the absolute value of manipulable accrued profits measured based on the modified Jones model is used to measure.
TMT heterogeneity	Gender heterogeneity (*TMTG*): percentage of female members; education heterogeneity (*TMTE*): percentage of members with a master's degree or higher; functional heterogeneity (*TMTF*): measured using the Blau index.
Firm size	*Size*, the natural logarithm of the enterprise's total assets at the end of the period.
Years of listing	*Age*, current year–listing year +1.
Level of financial leverage	*LEV*, total liabilities/total assets of the enterprise at the end of the period.
Nature of ownership	*SOE*, 1 for state-owned enterprises, 0 for other enterprises.
Profitability	*ROTA*, net profit/average total assets.
Ownership concentration	*S-D*, the shareholding of the first largest shareholder as a percentage of total shares.

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Correlation Analysis

Table 2 reports the results of the descriptive statistics and correlation analysis of the main variables. According to the descriptive statistics, it can be seen that the mean value of the level of the GT of enterprises (*GTFP*) is 1.213, and the standard deviation is 0.628, which indicate that the sample enterprises have carried out a certain degree of GT in general, and there is a considerable gap between enterprises. The standard deviation of DT intensity (*DT*) is 9.410, which indicates that the level of DT varies greatly among enterprises. The standard deviation and mean value of information asymmetry degree (*IA*) are 0.064 and 0.060, respectively, reflecting that the degree of information asymmetry and differences among enterprises are small. In addition, the data in the table also show a lower proportion of female members in TMT, a higher average level of education, and a greater variation in the functional background. From the results of the descriptive statistics, the sample data of certain indicators have large differences, and to reduce the impact of data fluctuations, clustering robust standard errors are used to adjust in the subsequent regression tests.

Table 2. Descriptive statistics and correlation analysis.

Variables	Mean	S.D.	GTFP	DT	IA	TMTG	TMTE
GTFP	1.213	0.628	1.000				
DT	6.551	9.410	0.316 ***	1.000			
IA	0.064	0.060	−0.010 **	−0.064 ***	1.000		
TMTG	0.160	0.102	0.433 ***	0.209 **	−0.020	1.000	
TMTE	0.710	0.183	0.287 *	0.170 **	−0.085	0.214 **	1.000
TMTF	0.700	0.094	0.105 *	0.211 *	−0.094 ***	−0.042	−0.148 **
Size	24.081	1.376	0.166 ***	0.151 **	−0.025	−0.329 **	0.028
Age	16.253	6.184	0.031 **	0.177 *	−0.056	0.013	0.151
LEV	0.511	0.180	−0.080	−0.045	0.029	−0.310	−0.154
ROTA	0.042	0.063	0.212 ***	0.105 ***	0.019	0.232 *	0.110 ***
S-D	0.432	0.152	−0.158 ***	−0.079	−0.058	−0.209 **	0.200
SOE	0.750	0.433	−0.065	−0.210 **	−0.135 *	−0.267 **	0.191
Variables	**TMTF**	**Size**	**Age**	**LEV**	**ROTA**	**SD**	**SOE**
Fun	1.000						
Size	0.272 **	1.000					
Age	0.069	−0.054	1.000				
LEV	0.080	0.456 *	−0.151 *	1.000			
ROTA	0.127	−0.044	0.006	−0.451 *	1.000		
S-D	−0.004	0.183	−0.299 **	0.046	0.078	1.000	
SOE	−0.049	0.135 **	0.311 ***	−0.037	−0.084	0.109 *	1.000

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Same as below.

The results of the correlation analysis show that there is a significant positive relationship between the intensity of DT and the level of the GT of enterprises, while the intensity of DT and the degree of information asymmetry and the degree of information asymmetry and the level of GT both show a significant negative relationship, which confirm the previous hypothesis to some extent. In addition, the covariance results show that the maximum value of the variance inflation factor (VIF) is 1.773 less than 5, and the tolerances are all close to 1, indicating that there is no serious problem of multiple covariances among variables.

4.2. Baseline Regression Results

Columns (1), (2), and (3) in Table 3 report the results of the core test of "DT intensity–T level". The univariate test results in column (1) show that the regression coefficients of the DT intensity (*DT*) and GT level (*GTFP*) are significantly positive at the 1% level, which is consistent with the expected hypothesis. The gradual inclusion of industry and time-fixed effects and the set of control variables in columns (2) and (3) reveal that the coefficients of DT intensity are reduced to 0.021 and 0.019, respectively, probably due to the set of control variables and certain inherent attributes of firms absorbing some of the factors affecting the GT of firms. After controlling for the endogeneity issues mentioned above, the regression coefficients of the two are still significantly positive at the 1% level, which indicates that the higher the degree of DT of manufacturing enterprises, the higher the level of GT, and the two show a significant positive correlation; H1 is verified. DT, due to its own characteristics, can bring important support to enterprises in terms of both a benefit-increase and environmental protection, so that enterprises can have enough revenue to help their survival and development while pursuing green development. At the same time, digital technology itself is a clean technology that can help enterprises continuously reduce energy consumption and pollution emissions while continuously improving the original R&D and manufacturing processes, which are conducive to promoting the occurrence of GT. The findings of this study are similar to those of Zhang and Liu [78] and Kunkel [79].

Table 3. DT and GT.

Variables	Baseline Return			Robustness Test 1		Robustness Test 2		Endogeneity Test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		GTFP		Ene	Pol			GTFP	
DT	0.025 ***	0.021 ***	0.019 ***	−0.003 ***	−0.006 ***				
	(4.87)	(5.16)	(4.46)	(−2.60)	(−3.56)				
DA						0.035 ***			
						(4.83)			
TP							0.026 ***		
							(3.16)		
L.DT								0.012 ***	
								(3.08)	
L2.DT									0.015 ***
									(3.48)
Size			0.040 ***	0.055 ***	0.065 ***	0.066 ***	0.043 **	0.047 **	0.048 ***
			(2.72)	(3.65)	(4.30)	(2.88)	(2.41)	(2.34)	(2.78)
Age			0.008 *	0.003 *	0.008 ***	−0.008 *	−0.007	−0.010 **	−0.014 **
			(1.96)	(1.65)	(4.09)	(−1.90)	(−1.59)	(−1.97)	(−2.31)
LEV			−0.085	0.309 ***	0.137	−0.062	−0.163	−0.084	−0.037
			(−0.41)	(3.48)	(1.48)	(−0.34)	(−0.77)	(−0.33)	(−0.13)
ROTA			1.865 **	0.027 **	−0.538 ***	1.789 ***	1.980 **	2.356 **	2.765 **
			(2.51)	(2.19)	(−3.01)	(2.63)	(2.37)	(2.25)	(2.21)
S-D			−0.714 ***	0.262 ***	0.331 ***	−0.847 ***	−0.685 ***	−0.856 ***	−1.028 ***
			(−3.40)	(3.29)	(3.41)	(−4.17)	(−3.23)	(−3.54)	(−3.78)
SOE			0.039	0.006	0.111 ***	−0.025	0.027	−0.023	−0.078
			(0.08)	(0.03)	(0.03)	(0.08)	(0.08)	(0.09)	(0.10)
_cons	−0.344 ***	−1.075 ***	−0.532 ***	−0.398 ***	−0.570 *	−0.052	−0.510 ***	−0.522 ***	0.696 ***
	(−13.64)	(−33.38)	(−8.50)	(−12.56)	(0.32)	(−1.06)	(−8.04)	(−6.97)	(−8.77)
N	560.000	560.000	560.000	560.000	560.000	560.000	560.000	490.000	420.000
R^2	0.198	0.300	0.370	0.297	0.288	0.279	0.246	0.325	0.222
adj.R^2	0.184	0.288	0.359	0.287	0.279	0.268	0.234	0.311	0.206
Industry	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The values in parentheses are the t-values adjusted for clustering robustness criteria errors. Same as below.

In terms of the control variables, the firm size (*Size*), the years of listing (*Age*), and the profitability (*ROTA*) are significantly positive, indicating that the larger the size, the more seniority, and the stronger the profitability of the enterprise, the more powerful it is to cope with the complex and changing green market and support the occurrence of GT; the ownership concentration (*S-D*) is negatively significant, indicating that the more decentralized the control of the enterprise, the flatter the structure, which is conducive to the enterprise grasping the dynamics of the green market and making timely decisions.

4.3. Robustness Tests

To test the persuasiveness and stability of the model, data, and indicators, the following three robustness tests are conducted in this paper.

1. Replace the metrics of the GT level. In this part, referring to the study of Dai et al. [4], the indicators of the GT level are decomposed into energy consumption intensity (*Ene*) and pollution emission intensity (*Pol*), and the regression analysis is re-run. If the explanatory variables show a significant negative correlation with the above two indicators, it means that DT can reduce energy consumption and pollution emissions, i.e., the level of GT increases. As shown in columns (3) and (4) in Table 3, the regression coefficients are significantly negative at the 1% level, indicating that the benchmark results are robust to some extent.
2. Decompose the indicators of DT intensity. Enterprise DT is a spectrum concept [17] that contains structural differences at the technology and model levels, so this paper regresses the level of GT on two dimensions of DT—technology penetration (*TP*) and digital adoption (*DA*)—as subindicators, respectively. The results in columns (5) and (6) in Table 3 show that the positive correlations between technology penetration and digital adoption and GT are both significant at the 1% level, as expected in this paper, and illustrate the robustness of the regression model.
3. Discussion of endogenous issues. While DT drives the occurrence of GT, the increased demand for technology improvement, market depth, and financing needs to be brought about by GT may also reverse the generation of DT. To overcome the possible reverse causality problem, the explanatory variables are treated with one and two lags (*L.DT*, *L2.DT*), respectively, in this paper, and the regression results are shown in columns (7) and (8) in Table 3, where DT still presents a highly significant positive contribution to GT (coefficients of 0.012 and 0.015, respectively, and significance at the 1% level), which is consistent with the main regression results. This indicates that there is no reverse causality between the two, which supports the hypothesis of this paper.

4.4. Further Analysis

4.4.1. Channel Effect Analysis

Given the problems of low efficacy and bias in the traditional channel mechanism test, this paper carries out the following treatments: (1) referring to Yu [80], a channel mechanism effect model with a cross-product term is used to conduct the test; (2) to avoid the problem of multicollinearity caused by the cross-product term, the data are centered (same as below); (3) considering the causal time lag of the indirect effects, the explanatory variables are treated with one period ahead, the channel variables are kept in the current period, and the explanatory variables are lagged one period behind, in order to overcome the endogeneity problem and further clarify the relationship between them. The test model is as follows:

$$IA_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \sum \eta Controls_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$GTFP_{i,t} = \beta_0 + \beta_2 DT_{i,t} + \beta_3 IA_{i,t} + \sum \eta Controls_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$GTFP_{i,t} = \beta_0 + \beta_4 DT_{i,t} + \beta_5 IA_{i,t} + \beta_6 DT_{i,t} * IA_{i,t} + \sum \eta Controls_{i,t} + \varepsilon_{i,t} \tag{5}$$

where *IA* represents the degree of information asymmetry. The connotation and names of other variables are the same as in model (2).

The results for the role of channels are reported in columns (1) to (3) in Table 4. The results show that DT significantly suppresses the increase in the degree of information asymmetry (regression coefficient of −0.001, significance level of 1%). This suggests that the degree of information asymmetry may play a transmission role in the relationship between DT and GT. The results of the test of the model (5), which is presented in column (3), show that the coefficient of the interaction term is −0.140 and significant at the 5% level, which indicates that the impact of DT on the GT of companies is mainly present in companies with high information transparency. It further indicates that the digitalization of manufacturing firms may promote the level of GT by reducing the degree of information asymmetry, and H2 is verified. In the new economy where "fast fish eat slow fish", the richness and fluency of information determine whether an enterprise can survive and grow in the fierce competition, and DT enhances the ability of enterprises to process massive, non-standardized, and unstructured data; promotes the release and exchange of information and resources; and increases the transparency of information between enterprises and stakeholders. It is conducive to building a green image, expanding funding sources, and providing motivation for companies to successfully conduct GT. This result combines the findings of Tian and Cheng [81] and Lin and Zhang [55] to illustrate the channel role of information asymmetry in terms of its antecedents and outcomes.

Table 4. Channel and mechanism role test.

Variables	Channel Test			Mechanism Test		
	(1)	(2)	(3)	(4)	(5)	(6)
	IA	GTFP		GTFP		
DT∗IA			−0.140 **			
			(−1.98)			
IA		−0.189 ***	−0.082 **			
		(−3.59)	(−2.40)			
DT	−0.001 ***	0.018 ***	0.016 ***	0.009 ***	0.014 ***	0.026 ***
	(−2.64)	(4.33)	(3.91)	(2.87)	(3.42)	(4.85)
DT∗TMTG				0.094 ***		
				(3.19)		
DT∗TMTE					1.041 ***	
					(6.33)	
DT∗TMTF						0.160 **
						(2.01)
TMTG				2.935 ***		
				(8.68)		
TMTE					0.007	
					(0.25)	
TMTF						0.557
						(1.40)
N	490.000	420.000	420.000	560.000	560.000	560.000
R^2	0.313	0.292	0.299	0.365	0.269	0.311
adj.R^2	0.268	0.277	0.282	0.352	0.254	0.295
CVs	Yes	Yes	Yes	Yes	Yes	Yes
_cons	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

4.4.2. Mechanism Role Analysis

To verify the effect of TMT heterogeneity, this paper introduces an interaction term to test the mechanism effect based on the main effect model. The test model is as follows:

$$GTFP_{i,t} = \beta_0 + \beta_7 DT_{i,t} + \beta_8 TMTX_{i,t} + \beta_9 DT_{i,t} * TMTX_{i,t} + \sum \eta Controls_{i,t} + \varepsilon_{i,t} \quad (6)$$

Among them, *TMTX* represents the three categories of TMT heterogeneity, and the connotation and names of other variables are the same as in model (2).

The regression results are reported in columns (4) to (6) in Table 4. The results show that TMT gender, educational background, and functional background heterogeneity all contribute positively to the process of DT driving GT (coefficients of 0.094, 1.041, and 0.160, respectively) and are each significant at the 1%, 1%, and 5% levels. This suggests that the impact of DT on corporate GT is mainly found in firms with high TMT heterogeneity. Specifically, the driving force of corporate DT on GT works better when there are more women in TMT, higher levels of education, and greater differences in functional backgrounds, validating H3. The results corroborate part of Hambrick and Mason's argument that high TMT heterogeneity brings more resources to the team, along with broader and closer ties to the outside world, and more innovative vision and actions. Based on the content of this paper, pro-environmentalism due to high gender heterogeneity, new technology inclusion due to high educational heterogeneity, and strategic foresight due to high functional heterogeneity become internal conditions for DT to drive GT, in which it plays an active role as a mechanism. This finding is similar to that of Ardito and Messeni Petruzzelli [82], Meng and Wang [68], and Chen and Hao [66].

4.4.3. fsQCA Equivalence Pathway Analysis

Unlike non-SOEs that pursue profit maximization, SOEs are usually established to achieve the purpose of state regulation of the economy and protection of people's interests and have a natural inseparable relationship with the government, so they will be more responsive to the national call for GT and take responsibility for sustainable development [7], and thus may present a better level of GT. In addition, different regions and industries where companies are located can have a differentiated impact on the effect of GT due to different levels of economic development, competition, and production policies. To further understand the multiple concurrent causalities of the GT of manufacturing enterprises and clarify the influence of different dimensional factors on the transformation mode, this paper adds ownership attributes to the original antecedent conditions and distinguishes the regions and industry categories where they are located, and uses the fsQCA method to explore the equivalence influence paths of GT and further explore the differentiated claims of GT. Since fsQCA cannot handle panel data and the possible lag of GT, the antecedent conditions and outcome variables are selected to analyze the static cross-sectional data of the sample firms in 2019 and 2020, respectively.

Data Calibration

Data calibration is an important step in an fsQCA analysis, through which the variable ensemble is assigned membership degrees that are structured and calibrated to an ensemble membership score of 0.0 to 1.0. Based on the sample data characteristics and related literature, the direct calibration method is used to anchor the full-set membership, intersection-set membership, and full-set non-membership of the variable sets at 75%, 50%, and 25% [83,84]. The calibration results are shown in Table 5.

Necessity Analysis of Individual Conditions

The necessity test focuses on how dependent the generation of the outcome variable is on a certain antecedent condition (or set), in which we focus on the consistency level of each condition and condition cluster. If a consistency level of 0.9 is not reached, the outcome set is considered not to be a subset of the condition set. The results reported in Table 6 show that the antecedent conditions (including the non-set) have a consistency maximum of 0.752 and the rest of the values are less than 0.9, i.e., they do not constitute a necessary condition for a high level of GT. This indicates that the explanatory power of individual conditions for high GT levels is weak, and therefore it is necessary to investigate the effect of grouping multiple antecedent conditions.

Table 5. Data calibration.

Condition Set		Calibration		
Antecedents and Results	**Target Set**	**Full-Set Membership**	**Intersection-Set Membership**	**Full-Set Non-Membership**
Green transformation	High level of green transformation	0.958	1.305	1.828
Digital transformation	Strong digital transformation intensity	3	5	9.25
Information asymmetry	High level of information asymmetry	0.01	0.04	0.06
TMT gender heterogeneity	High TMT gender heterogeneity	0.088	0.18	0.28
TMT education heterogeneity	High TMT education heterogeneity	0.685	0.8	0.88
TMT functional heterogeneity	High TMT functional heterogeneity	0.698	0.75	0.78
Ownership properties	State-owned enterprises	1		0

Table 6. Necessity analysis of individual conditions.

Conditions	High Level of Green Transformation	
	Consistency	**Coverage**
Digital transformation	0.709	0.732
~Digital transformation	0.416	0.422
Information asymmetry	0.569	0.557
~Information asymmetry	0.527	0.539
TMT gender heterogeneity	0.701	0.714
~TMT gender heterogeneity	0.491	0.484
TMT education heterogeneity	0.612	0.601
~TMT education heterogeneity	0.463	0.472
TMT functional heterogeneity	0.541	0.559
~TMT functional heterogeneity	0.573	0.556
State-owned enterprises	0.752	0.568
~State-owned enterprises	0.148	0.256

Configuration Analysis

The configuration analysis will identify the driving patterns of high GT levels. Firstly, in the setting of the frequency threshold, the case data are a medium sample (70 cases), so the frequency threshold is set to 1.25 [85]. Secondly, in the setting of the consistency threshold, the natural break point of the data column 0.799 is set as the consistency threshold in combination with the requirement of the minimum recommended value of 0.75 for the PRI consistency threshold [84]. The condition "Present or Absent" is chosen in the process of deriving the solution because there is no necessary condition in the prior. Table 7 shows the results of the histological analysis based on the parsimonious and intermediate solutions.

Table 7. Configuration analysis results.

Conditions and Case Characteristics	High Level of GT			
	Configuration 1	**Configuration 2**	**Configuration 3**	**Configuration 4**
DT	●	●	•	•
IA	⨂	⊗	⊗	
TMTG	●		●	●
TMTE		●	•	●
TMTF		⊗		•
SOE	•	●	⨂	⨂
Consistency	0.882	0.834	0.930	0.857
Raw coverage	0.306	0.236	0.107	0.034
Unique coverage	0.216	0.106	0.059	0.024
Solution consistency	0.879			
Solution coverage	0.545			
Typical case areas	Eastern Region	Eastern Region	Central and Western Region	Central Region

Table 7. *Cont.*

Conditions and Case Characteristics	**High Level of GT**			
	Configuration 1	**Configuration 2**	**Configuration 3**	**Configuration 4**
Typical case city and province	Shanghai, Shandong Province	Jiangsu Province, Zhejiang Province	Shanxi Province, Yunnan Province	Anhui Province
Typical case industries	Chemical raw materials and chemical products manufacturing; ferrous metal smelting and rolling processing industry	Computer, communications, and other electronic equipment manufacturing; pharmaceutical manufacturing	Petroleum processing, coking, and nuclear fuel processing industry; non-ferrous metal smelting and rolling processing industry	Electrical machinery and equipment manufacturing

● indicates that the core condition exists; ⊗ indicates that the core condition is missing; • indicates that the auxiliary condition exists; ⊗ indicates that the auxiliary condition is missing; blank indicates that the presence or absence of the condition does not affect the result.

The results in Table 7 show that there are four driving paths with high GT levels. The consistency level of the four groupings and the overall solution is higher than 0.8, and the coverage is higher than 0.5, indicating that the degree of consistency and the explanatory strength of the solutions are relatively good, and the interpretation of the GT driving model is relatively strong. The specific histories are analyzed as follows:

First, both configuration 1 (DT*~IA*TMTG*SOE) and configuration 2 (DT*TMTG*TMTE*~TMTF*SOE) reflect the central role of DT and TMT heterogeneity in enterprises. Configuration 1 shows that a high level of DT, weak information asymmetry, and high TMT gender heterogeneity will lead to a high level of GT in manufacturing firms, and the role of this configuration is more pronounced in state-owned enterprises. This path covers 30.6% of the number of cases and is the main configuration that forms a high level of GT. The core conditions of configuration 2 shift to DT, TMT education heterogeneity, and SOEs compared to configuration 1. This path covers 23.6% of the number of cases and is the secondary construct that forms a high level of GT. Configuration 2 shows that DT better empowers GT in SOEs with higher executive education backgrounds. In addition, in terms of the industry and region, these two configurations are mainly generated in manufacturing enterprises in eastern regions such as Shanghai and Jiangsu, and concentrated in heavily polluting industries such as chemical and metallurgical industries ① and high technology industries such as pharmaceuticals and computers ②. Combining the two groupings, SOEs have access to digital resources from the government in addition to market data due to their special status [7]. When TMT educational background heterogeneity and gender heterogeneity are higher, the team is more capable of learning, ethical awareness, strategic vision, and pro-environmental, and more capable of processing and utilizing complex data, and thus confident to proactively implement green strategies [48]. Further, when the economic and digital development of the region is high ③, the digital empowerment for enterprises is stronger and can weaken the degree of information asymmetry between supply and demand. When the people's demand for product quality and better life is higher, then the pull of the green product market is stronger and can help heavy polluting and high technology enterprises to reduce resource consumption and pollution emissions and take steps toward GT.

Secondly, configuration 3 (DT*~IA*TMTG*TMTE*~SOE) and configuration 4 (DT*TMTG*TMTE*TMTF*~SOE) reflect the high TMT gender heterogeneity, higher level of DT, and the important role of educational heterogeneity in the GT of non-SOEs. These two paths cover less intensity, but also provide unique GT ideas for non-SOEs. In addition, in terms of industries and regions, these two configurations are mainly generated in traditional industries and heavily polluted industries in central and western regions such as Shanxi, Yunnan, and Anhui. This indicates that although non-state enterprises are equally committed to green development, the external drivers of corporate GT are not strong in the central and western regions, where economic development and digitalization lag behind the eastern regions due to fewer high-tech industries, less marketization, and a lack of talents [2].

Under such circumstances, the emphasis on the practical relationships and responsibilities of female executives will make them pay more attention to the environmental demands of stakeholders and the green image of the company [73], relative to short-term interests, and tend to green development.

Synthesizing the different paths of high GT levels reveals that DT plays a central conditional role (including core and auxiliary causality) in high GT levels, and information asymmetry, TMT gender heterogeneity, and educational background heterogeneity play important roles, verifying the plausibility of the results of the main regression analysis in the case of multiple causalities. The failure of TMT functional heterogeneity to be the main condition may be because, in the outcome-oriented fuzzy set analysis, the relationship between variables changes from mutually independent net effects to interdependent complex causal relationships, in which the effect of TMT functional heterogeneity is weakened, and absorbed, and only plays a supporting role in specific contexts.

5. Conclusion and Discussion

The GT of enterprises is a microscopic requirement of "accelerating the GT of development" ④. In the context of the rapid development of the digital economy and increasing digitalization level of enterprises, it is important to study the impact of DT on GT for China to practice the governance concept of "lucid waters and lush mountains are invaluable assets" and high-quality economic transformation. DT not only has a significant impact on the economic value creation of enterprises, but also promotes the implementation of green strategies by improving data capabilities, promoting business model innovation, and improving resource allocation efficiency [46,48]. However, there is little evidence in the literature that examines the fundamental relationship between DT and GT. Moreover, the theoretical framework and boundary conditions that influence the effectiveness of GT in firms remain unknown. Therefore, this paper uses a sample of 70 A-share-listed manufacturing companies in China from 2013 to 2020 and uses a combination of linear regression and fsQCA based on the STS framework to empirically test the research model and equivalence path analysis. The aim is to fill the gaps in the existing literature by examining the impact relationship between DT and GT, the channel and mechanism roles of information asymmetry and TMT heterogeneity in it, and the driving model of GT. We obtain several interesting results.

First, DT has a significant positive effect on manufacturing firms' GT. This finding is consistent with Xiong [8] and Kunkel [79]'s view. Previous micro studies have focused on the role of Industry 4.0 in improving the sustainability of supply chain management, green technology, and environmental performance [45,47], but lacked an exploration of the direct impact mechanism of DT on GT. This study confirms that DT can help manufacturing enterprises to achieve a GT leap, and then form a new model of "digital + green" integration development [48,68], so that enterprises can achieve a harmonious integration of environmental protection, business development, and social responsibility.

Second, information asymmetry acts as a channel between DT and GT. When companies effectively promote DT, they have the ability to increase green information disclosure and broaden information transmission channels to reduce the degree of information asymmetry between systems. In turn, they can gain more competitive advantages and development resources and reduce the risk of GT in the process of enhancing interaction and transmitting signals [54,86]. This finding not only connects the relationship of DT to information asymmetry and information asymmetry to GT in previous studies [55,81], but also confirms the channel role played by information asymmetry between DT and GT, and further verifies the path of DT influencing GT.

Third, TMT heterogeneity (including gender, educational background, and functional background heterogeneity) plays a positive mechanism role in the relationship between DT and GT. Meng [68] argues that the DT of firms plays a positive mechanism role between TMTs' overseas experience of heterogeneity and green innovation. However, the role of TMT heterogeneity between DT and GT is still unknown. This paper argues that the high gender heterogeneity of TMT brings a more inclusive leadership style and greater acceptance of digital change [87], which in turn paves the way for high-risk GT [68]. The high education of TMT members also increases their advantage in weighing the pros and cons of DT and raises stakeholders' expectations of GT [66,88]. This is similar to Chen's view [66]. In addition, Liu [67] argues that the differentiation of TMT functions may contribute to improvements in the green dynamic capabilities of firms, but no rigorous empirical results are available to prove this. The results of this paper confirm that companies with a high heterogeneity of TMT functions are prone to constructive debates, have a positive impact on the transformational change aspects of the organization, and better perceive the green opportunities brought by digitalization.

Through further qualitative comparative analysis, the following is concluded:

First, the main constructs that shape the high level of GT in manufacturing enterprises are high DT intensity, low information asymmetry degree, and high TMT gender heterogeneity. This path mainly arises in the eastern region, and the role is more obvious in state-owned enterprises, heavy pollution, and high-tech industries, and this path demonstrates the important coordination effects of DT, information asymmetry, TMT gender heterogeneity, and enterprise. This path shows the important coordination effect of DT, information asymmetry, TMT gender heterogeneity, and firm ownership on promoting GT, consistent with the main regression results of this paper.

Second, for non-SOEs in traditional industries in central and western regions with average digital development, high TMT gender heterogeneity is a key condition for GT. Combined with the previous construct, this reflects the existence of a stronger driving force for GT among female executives in manufacturing firms undergoing DT, regardless of the level of digitalization, a finding similar to Islam [89] and Chen [66].

This study introduces the fsQCA analysis, which to a certain extent compensates for the drawbacks of causal symmetry in the linear regression analysis, and further proves the reliability of the paper's conclusions. Additionally, the findings specific to regions, industries, and ownership provide a basis for practical insights. Moreover, the effect of TMT functional heterogeneity shows different results from the regression analysis, possibly due to the reduced perceived usefulness of TMT functional heterogeneity when the variables are transformed into interrelated conditional clusters to be tested [84], thus reflecting the presence, but weaker usefulness, of TMT functional heterogeneity in GT practice.

6. Practical Implications

This paper clarifies the relationship between the DT and GT of enterprises with the help of the STS theoretical framework, which has important insights for the advantage of digital efficiency and low-carbon transformation of manufacturing enterprises in the new era.

1. The results of both the regression analysis and fuzzy set analysis show that DT is the core condition to promote the GT of manufacturing enterprises, and it achieves the harmonious unification of industrial development and environmental protection through digital empowerment. Therefore, China should follow the development trend of digitalization and accelerate the construction of new infrastructures such as 5G base stations, data centers, smart energy, and industrial Internet to provide technical guarantees for the DT of enterprises. At the same time, the government should give the necessary financial support and policy encouragement to enterprises in transition to ease the pressure and difficulties they encounter. Enterprises should also be aware of the huge impetus brought by DT, and take the initiative to respond to the policy call to promote the deep integration of digital technology and the whole process of manufacturing practices to accelerate the occurrence of GT.
2. This study shows that DT may contribute to a higher level of GT by reducing the degree of information asymmetry. The role of the low information asymmetry degree as one of the main core conditions for a high GT level is also verified in the fuzzy set analysis. Based on this, the country should establish a sound data-sharing and information disclosure system to form a pattern of collaborative governance and

information-sharing, and to promote the driving role of data and information on production development. In addition, it should also strengthen the system construction and regulatory enforcement of information protection to ensure the privacy and security of information in the whole process of source, channel, and host dissemination and prevent malicious leakage and use. For enterprises, they should establish the concept of collaborative sharing; build a digital information-sharing platform; take the initiative to disclose information to stakeholders such as the government, employees, consumers, media, and partners; embed digital technology in the whole chain of R&D, production, sales, and services; and reduce the cost of green product search and adverse selection due to information asymmetry.

3. TMT heterogeneity is also an important factor for high GT levels, especially gender heterogeneity and educational background heterogeneity, which show high correlation and causality in both the regression analysis and fuzzy set analysis; however, the statistical analysis shows that the proportion of female executives in Chinese manufacturing enterprises is still at a low level, and their role in promoting sustainable development is not valued. Therefore, companies in GT should pay more attention to the composition of TMT, include more female members and members with higher education levels in the selection and recruitment, and play the leading role of female talents and high-quality talents in green development.
4. The fuzzy set analysis shows that high GT-level paths are distributed in different industries, regions, and enterprise ownership; therefore, manufacturing enterprises and governments should choose green development configurations according to local economic characteristics and resource endowments, and according to local conditions. Specifically, they should take a holistic perspective on the set of conditions, focus on the synergy of social and technological systems, formulate green strategies in a targeted manner, and choose differentiated paths for GT. For example, in the eastern region with a high digitalization and economic level, manufacturing enterprises can make full use of the advantages of technology, talents, resources, location, and policies to develop high-precision green enterprises and industries with international leading levels, and lead the synergistic development of the surrounding industrial clusters, especially the heavy pollution and high-technology state-owned enterprises. Secondly, in the central, western, and northeastern regions, on the one hand, efforts should be made to promote the TMT of traditional non-state-owned enterprises in the direction of females, to increase the number of women and improve their education, fully absorb the green development suggestions of female executives, and enhance their decision-making voice; on the other hand, efforts should be made to actively explore digital models suitable for local development, i.e., the central region can rely on the population advantage to develop digital consumption and distribution industries, and the western region can rely on the energy advantage to develop comprehensive intelligent energy, etc.

7. Limitations and Future Research Agenda

Although this paper has conducted multi-level research on theory and practice, there are still limitations and shortcomings, and we need to continue to deepen the exploration of the mechanism of DT on GT. First, there are sample selection and capacity issues. This study selects survey data from 70 manufacturing enterprises for 8 consecutive years, and future studies can try to conduct research in other types of enterprises such as construction, electricity and heat supply, and service industries to explore the differences in the effects of data-enabled GT in industries with different pollution generation and energy consumption profiles. At the same time, the number of samples and years can be expanded to study the characteristics, performance, and green effects of DT in different regions. Second, this study uses information misalignment as a channel and TMT heterogeneity as a mechanism to reveal the intrinsic path of manufacturing enterprises' DT impact on GT, which mainly involves the interaction between people and systems and between systems. In addition to the above paths, the more diverse ways in which non-industrial enterprises act after moving away from the production and manufacturing model may be issues worthy of further in-depth exploration in subsequent studies. Third, although this paper explores the role of DT in the relationship between systems, the future digitization of enterprises will develop in the direction of collaboration, openness, and integration, and resource integration and sharing will become the trend. Therefore, exploring the outsourcing of business modules (such as production and R&D) by manufacturing enterprises with the help of digital technology, developing toward more sustainable service, and conducting cross-platform, cross-time, and cross-region digital integration management, will be an important direction for research. Finally, this paper uses a combination of a linear regression and fuzzy set analysis to conduct the research, which to some extent makes up for the shortcomings of both sides. In the future, we can continue to compare the results of different data analysis techniques and use the combination of horizontal and vertical research methods to fully clarify the hidden laws in the results and improve the credibility and discussion of the research results.

① The identification of heavily-polluting industries is based on the List of industries for environmental verification and management of listed companies formulated by the Ministry of Environmental Protection in 2008, and the Environmental information disclosure guidance for listed companies, which mainly includes 16 categories of industries such as thermal power, iron and steel, cement, electrolytic aluminum, coal, metallurgy, chemical, petrochemical, building materials, paper, brewing, pharmaceutical, fermentation, textile, tannery, and mining.

② High-tech industries are identified according to the criteria of the High-tech industry (manufacturing) classification (2017), which includes 6 major categories such as pharmaceutical manufacturing, aviation, spacecraft and equipment manufacturing, electronics and communication equipment manufacturing, computer and office equipment manufacturing, medical instruments and equipment and instrumentation manufacturing, and information chemicals manufacturing.

③ According to the China Regional Digital Development Index Report, the top ten provinces and cities in terms of regional digital development level in 2020 are Guangdong, Zhejiang, Beijing, Jiangsu, Shanghai, Shandong, Sichuan, Fujian, Chongqing, and Shanxi; the bottom ten provinces and cities are Heilongjiang, Jilin, Xinjiang, Gansu, Shanxi, Tibet, Inner Mongolia, Qinghai, Guangxi, and Ningxia.

④ Excerpts from the report of the 20th National Congress of the Communist Party of China.

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