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Digital transformation and corporate green innovation: An affordance theory perspective

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Abstract

The rise of cutting-edge technologies motivates corporations to undertake and carry forward green innovation, aiding economic development by maintaining environmental sustainability. Using A-share listed firms from 2013 to 2022 as the research sample, the paper empirically examines the impact of digital transformation on corporate green innovation from an affordance perspective. The findings suggest that the higher the level of digital transformation, backed by accumulative and variational affordances, in a firm, the more conducive it is to corporate green innovation as it enables the homogenization, recombination, and transformation of existing information related to green environmental protection and low-carbon energy efficiency, facilitating firms to achieve targeted and breakthrough green innovations. The analysis of the moderating effects of public environmental concern, economic policy uncertainty, and regional innovation readiness suggested that public environmental concern and regional innovation readiness positively moderate the relationship between digital transformation and corporate green innovation, while economic policy uncertainty perception negatively moderates this relationship. Heterogeneity analyses suggest that digital transformation positively affects corporate green innovation within labor-intensive firms and state-owned enterprises. The study contributes to the literature by enhancing our understanding of the affordance theory in the domain of digital transformation. By investigating the key organizational and institutional affordances – economic policy uncertainty perception, public environmental concern, and regional innovation readiness – the research provides valuable insight to policymakers in fostering green innovation.

KEYWORDS

affordance theory, digital transformation, economic policy uncertainty perception, green innovation, public environmental concern, regional innovation readiness

1 | INTRODUCTION

The emergence of the digital economy, fueled by cutting-edge technologies such as machine learning, big data, distributed ledger, and internet-based computing, transforms traditional industries, optimizes

Abbreviations: 2SLS, two-stage least squares; AI, artificial intelligence; CGI, corporate green innovation; CNRDS, China Research Data Services Platform; CSMAR, China Stock Market and Accounting Research; DT, digital transformation; EPU, economic policy uncertainty; ESG, environmental, social, and governance; FDT, frequency of digital transformation; GPAT, green invention patent applications; IoT, Internet of Things; IV, instrumental variable; PEC, public environmental concern; R&D, research and development; RIR, regional innovation readiness; SOEs, state-owned enterprises; ST, special treatment.

resource allocation, and enhances production efficiency (Bai et al., 2020; Nayal et al., 2022; Shaik et al., 2024; Sun et al., 2023). This shift toward a digital economy reduces operational costs, overcomes research and development (R&D) challenges, and supports the transition to low-carbon and green development methods (Hanelt et al., 2021; Kumar et al., 2021; Li, 2022; Mariani et al., 2023). The intersection of digital transformation (DT) and corporate green innovation (CGI) represents a critical juncture for businesses to navigate contemporary challenges in the world of sustainability and digitalization. The necessity for firms to innovate in the green direction, driven by regulatory pressures and environmental concerns, is well established. However, what motivates the current study is the under-explored role of DT in facilitating this shift, particularly in how digital affordances (accumulative and variational) contribute to CGI.

Existing literature has extensively explored the relationship between digital transformation (DT) and CGI (Kohtamäki et al., 2020; Zheng & Zhang, 2023). Scholars argue that DT is vital in promoting green technological innovation within firms (Dou & Gao, 2023; Ghobakhloo et al., 2021; Liu, Chen, & Liang, 2023). They suggest that DT enhances innovation efficiency, improves environmental, social, and governance (ESG) performance, drives green transformation, and boosts green economic efficiency (Deng et al., 2024; Jin et al., 2024; Tang et al., 2023). Another set of studies has identified factors influencing the impact of DT on promoting CGI (Chen, 2023; Shao & Xu, 2024), including internal organizational dynamics and external institutional influences, such as dynamic capabilities, resource allocation levels, information disclosure practices, environmental regulations, and institutional pressures (Ai et al., 2024; Gao et al., 2022; Martinez Hernandez et al., 2021; Sendstad & Chronopoulos, 2020; Upadhayay et al., 2024; Xu, Yu, et al., 2023; Xu, Yuan, et al., 2023).

Though there have been many studies on the direct impact of DT on various forms of innovation, the specific pathway through which DT promotes CGI remains under-explored (Habib, 2023). Based on the literature studied, one of the areas of the gap that the current study plugs in is how specific digital affordances, such as accumulative and variational, enable CGI. Further, previous studies have overlooked the contextual factors that may moderate the relationship between DT and CGI. The influence of external factors, like economic policy uncertainty, public environmental concern, and innovation readiness, has yet to be adequately explored (Gong et al., 2024). The current study further fills this gap by examining these factors' moderating effects to better understand the complexities surrounding DT and CGI, offering theoretically novel and practically relevant insights. To cater to these research gaps, the current paper addresses the following questions:

RQ 1. Why do digital transformation opportunities enable firms to pursue CGI?

RQ 2. Under what institutional backgrounds or circumstances can the potential benefits of promoting corporate green innovation through digital transformation be realized?

To address the proposed research question, the current study draws upon the nuances of affordance theory proposed by psychologist Gibson (1979; adapted to technological applications) to describe how technology objects enable the achievement of predetermined goals. Unlike other technology theories, affordance theory offers a valuable research framework for investigating DT and CGI. It emphasizes the importance of a balance between “actors” and “technology” – while technology provides possibilities, it does not directly produce results (Li, Xu, et al., 2023). Affordance theory indicates that digital technologies possess affordances, creating opportunities for CGI through DT (Li, Zhou, et al., 2023); hence, firms prioritizing sustainable practices can leverage DT to foster CGI potential (Liu, Liu, & Ren, 2023; Li, Xu, et al., 2023; Rahmani et al., 2024).

The current study has chosen Chinese firms as its subject to explore the relationship between DT and CGI with other relevant moderating factors. The choice is based on the fact that the Chinese government has prioritized greening through digitization (Luo et al., 2023; Sun et al., 2023). This can be seen through the call by the Chinese government through its “Fourteenth Five-Year National Informatization Plan”, which promotes green smart ecological civilization construction and advancing the coordinated development of digitization and greening, thus realizing the harmonious coexistence of economic growth and environmental responsibility (Chen et al., 2024; Chen & Liang, 2023).

The contribution of this article lies in several aspects. Firstly, while existing literature primarily discusses the impact of DT on CGI through lenses such as resource allocation, dynamic capabilities, and innovation diffusion, this article takes an affordance perspective. It validates how DT promotes CGI using the “context-mechanism-outcome” logic (Thomas et al., 2016). It offers a fresh perspective and approach to understanding corporate DT and reaping digital dividends. Secondly, it aims to uncover the mechanisms through which DT drives CGI by considering the perceived uncertainty of economic policies by firms, public environmental concerns, and regional innovation readiness. This broadens the research on factors driving CGI and practically enhances the success rate of DT efforts. Lastly, this study delves into the heterogeneous effects of DT on CGI among firms with different ownership and production factor intensities. It finds that DT has the most notable impact on CGI in state-owned enterprises (SOEs) and labor-intensive firms. This furnishes empirical evidence for crafting tailored digital economic policies to foster CGI.

The rest of the paper is structured as follows: the introduction is followed by the theoretical analysis and hypotheses section, followed by the section on the data and methodology adopted for the study. The next section discusses the results, followed by the conclusion and implications sections.

2 | THEORETICAL ANALYSIS AND HYPOTHESES

2.1 | Affordance theory

Psychologist Gibson (1979) first introduced the term “affordance” in the field of ecological psychology, which has since been applied to explain behavioral possibilities in various environments and extended to technological contexts (Norman, 2013). Technology affordance extends beyond mere functionality; it delves into the potential actions and outcomes enabled by a given technological tool (Majchrzak & Markus, 2013; Volkoff & Strong, 2013). From a technology affordance perspective, DT provides potential for CGI among firms committed to sustainable development. In other words, CGI is viewed as a progression from recognizing potential "affordances" to realizing them (De Luca et al., 2021; Dremel et al., 2020; Strong et al., 2014) with CGI outcomes representing the actualization of these affordances.

It is important to note that while technology affordances can stimulate CGI, different users operating the same technology in diverse contexts may yield diverse CGI outcomes. The achievability of CGI hinges not only on digital technology affordances but also on organizational and institutional affordances, which encompass internal management within firms, institutional frameworks, and regional infrastructures (Chatterjee et al., 2020; Pinkse & Bohnsack, 2021; Pitafi et al., 2023). Organizational affordance refers to organizations' inherent resources, capabilities, and structures, enabling them to perceive and act upon opportunities and challenges in their external environment (Lokuge et al., 2019). Institutional affordance refers to the opportunities, constraints, and possibilities shaped by institutional structures and norms within a particular organization or system (Van Dijk et al., 2011). It is the extent to which an institution's rules, resources, and practices enable or constrain specific actions or behaviors by individuals or groups.

Drawing from institutional theory and the work of Zobel et al. (2017), this study categorizes institutional affordance into informal and formal categories. Informal institutional affordances are not explicitly stated in formal rules or regulations but emerge through social dynamics and cultural norms. In contrast, formal institutional affordances provide a structured framework guiding societal behavior, processes, and interactions. Formal institutions' affordance lies in their potential capability to promote accountability, fairness, and societal organization. Especially in developing countries where organizational and regional institutional landscapes are evolving, DT must surmount these barriers to foster CGI. This article seeks to elucidate how DT influences CGI and explores the interplay between firms and their internal and external environments.

2.2 | Digital transformation and corporate green innovation

Digital technology affordance is defined as consisting of accumulative affordance and variational affordance, highlighting the interactive relationship between digital technology and business entities (Chatterjee et al., 2021; Nambisan et al., 2019; Wang & Juo, 2021). The emergence of new DTs like artificial intelligence (AI), Internet of things (IoT), blockchain, and big data provides firms with new ways to innovate. These technologies offer and support accumulative affordance, where incremental process improvements can drive green innovation by enhancing resource utilization and reducing waste (Qin, 2023). The ability of accumulative affordance to gradually build upon the existing capabilities using DT leads to resource optimization, thus opening the avenues for more sustainable operations over time (Dou & Gao, 2023).

Further, the accumulative affordance of digital technology may facilitate information processing in firm operations, driving targeted improvements in the level of CGI within the firm (De Luca et al., 2021; Liu & Kong, 2021). Specifically, it enables firms to access various data channels comprehensively (Song et al., 2024), collect environmentally friendly data such as green conservation and low-carbon energy, and standardize and categorize existing information. When the accumulated information reaches a certain threshold, firms can utilize this feedback to innovate products, production processes, and organizational management (Aftab et al., 2023; Gao, Cheng, & Sun, 2023). This catalyzes CGI, which enhances operational efficiency, boosts market competitiveness, and encourages sustainable practices like energy conservation, environmental protection, and low carbon emissions (Nambisan et al., 2019).

In contrast, variational affordances allow for more radical innovation by enabling firms to redesign their business models and processes (Liu, Dong, et al., 2023). DT, like AI and blockchain, can disrupt traditional operations, allowing for more novel ways to support CGI (Zhang et al., 2024). Firms can improve the output efficiency of R&D investments by employing intelligent and specialized collaborative production methods, programming and transforming relevant programs and components (Loeser et al., 2017), enhancing green infrastructure, optimizing processes related to CGI such as product development, supply networks, and manufacturing, and reshaping the value creation logic for firms (Li, Zhou, et al., 2023). This injects new momentum into CGI for firms.

Studies have depicted that firms' effective leveraging of DT, be it accumulative or variational, has led to better achieving of green innovation than otherwise (Liu, Dong, et al., 2023; Rao et al., 2022). For instance, digital platforms and finance have shown promising results for contributing to CGI by improving transparency and reducing financial constraints (Liu, Mao, et al., 2023; Rao et al., 2022). DT promotes organizational learning to the next level, where firms continuously adapt and refine their processes to support and enhance CGI (Feng et al., 2024). As a result, the first research hypothesis of this study is proposed.

H1. DT can promote CGI in firms.

2.3 | Organizational affordance: economic policy uncertainty perception by firms

Organizations can leverage their understanding and interpretation of economic policy uncertainty as an organizational affordance to shape their strategies and actions (Zhang et al., 2023). A shift in firms' perception of economic policy uncertainty will result in alterations in decisions regarding DT and CGI (Li et al., 2024; Shao & Xu, 2024). Economic policy uncertainty often leads firms to adopt conservative approaches, restraining them from investing in new DTs (Kong et al., 2022). These restraining approaches can act as deterrents to digital affordances crucial for CGI, negatively moderating DT. Hence, firms operating under uncertainty are more likely to concentrate on short-term gains, thus limiting the effect of DT on CGI (Mirza & Ahsan, 2020; Novelli & Spina, 2024).

Research has shown that firms facing the perception of high economic uncertainty make trade-offs between the adoption of types of innovation, often sacrificing CGI, which requires comparatively more time to yield returns in favor of short-term and cost-saving innovations (Zhong et al., 2023). Uncertainty in economic policies stifles firms' commitment to continue with DT that supports CGI (Fan et al., 2023). This cautious approach negatively impacts the effect of DT on CGI. Furthermore, the uncertain perception of economic policy may affect decision-makers who, rather than investing in CGI, start to prefer cash flow and liquidity preservation (Huang et al., 2023). The firms tend to prioritize short-term survival over long-term innovation goals, reducing resource allocation to DT and leading to CGI (Jumah et al., 2023). This behavior, in turn, weakens the positive relationship between DT and CGI. Hence, we hypothesize:

H2. The perception of economic policy uncertainty in firms negatively moderates the impact of DT on CGI in firms.

2.4 | Informal institutional affordance: public environmental concern

As an informal institutional affordance, public environmental concern refers to the level of focus those investors, consumers, and social media direct toward firms (He et al., 2022). When firm behavior affects people's daily lives and productivity, the public intensifies its supervision to safeguard their rights and interests, especially in advancing eco-friendly lifestyles and sustainable consumption practices (Tao et al., 2023). This heightened public scrutiny is a crucial external supervision mechanism, exerting intangible pressures on firms to leverage DT to enhance their CGI efforts (Xie & Qi, 2024), promoting sustainable development.

Further, public concern toward sustainable development may shape the firm's social license to operate, thus promoting firms to better utilize their DT to implement CGI, hence maintaining their social legitimacy and customer base (Litvinenko et al., 2020; Saeed & Riaz, 2021). This, in turn, leads to better engagement with stakeholders, particularly showcasing their CGI efforts, thus building trust and enhancing their brand.

The rising public concern for environmental issues drives firms to differentiate themselves by adopting CGI strategies. DT catalyzes firms to adopt these initiatives effectively (He et al., 2023). DT provides the necessary infrastructure for these initiatives, making it possible to integrate new technologies into the existing processes (Zhang et al., 2023). Furthermore, firms that recognize the long-term public environmental concern try to align their DT initiatives with long-term environmental goals, thus supporting CGI outcomes. Firms are knowledgeable enough to recognize that public concern for the environment influences consumer preferences (Kuokkanen & Sun, 2020). So, a firm that consistently demonstrates the commitment toward CGI aided by DT would gain a competitive advantage. Hence, we hypothesize:

H3. Public environmental concern positively moderates the impact of DT on CGI in firms.

2.5 | Formal institutional affordance: regional innovation readiness

Regional innovation readiness pertains to a region's capacity to leverage resources such as talents, information, and knowledge to develop new products, processes, and technologies, particularly in CGI (Erdiaw-Kwasie & Abunyewah, 2024; Lau & Lo, 2015; Pan et al., 2020).

Regions with vital innovation ecosystems provide the necessary infrastructure, networks, and policies that promote DT (Guzman et al., 2024), thus supporting innovation readiness by providing robust talent aggregation capabilities that lead to significant spillover effects (Beynon et al., 2023). Particularly noteworthy is the ability of highly skilled technology professionals within these regions to assimilate and adapt existing technologies and foster the creation of new technological solutions that drive CGI (Sun & Li, 2022). During DT, cities with heightened innovation readiness can effectively address the demand for digital talent, mitigate shortages in digital talent supply, and strongly support CGI efforts (Carfora et al., 2021; Ma & Li, 2022).

Regional innovation readiness is backed by strong collaborative networks that foster relationships between firms, research centers, and government agencies, facilitating knowledge exchange and joint initiatives supporting DT by sharing costs, knowledge, and talents (Wang & Juo, 2021). Regions with proactive regulatory environments enable firms to innovate more freely and align their DT with CGI (González-López & Asheim, 2020; Sebaka & Zhao, 2023). Innovation-ready regions often support a strong financial market system wherein financial resources are adequate to support DT and CGI, thus amplifying the effect of DT (Jung et al., 2023). Further, such regions have opportunities for public-private partnerships, creating a supportive environment for DT and CGI (Xu & Wudi, 2024). Innovation-ready regions are delineated by the support of government agencies and formal institutions, which ensures that the firms have the necessary resources and framework to pursue DT and CGI (Zhang & Rodríguez-Pose, 2024). Based on the argument, we propose the fourth hypothesis:

H4. Regional innovation readiness positively moderates the impact of DT on CGI in firms.

Figure 1 presents the theoretical framework.

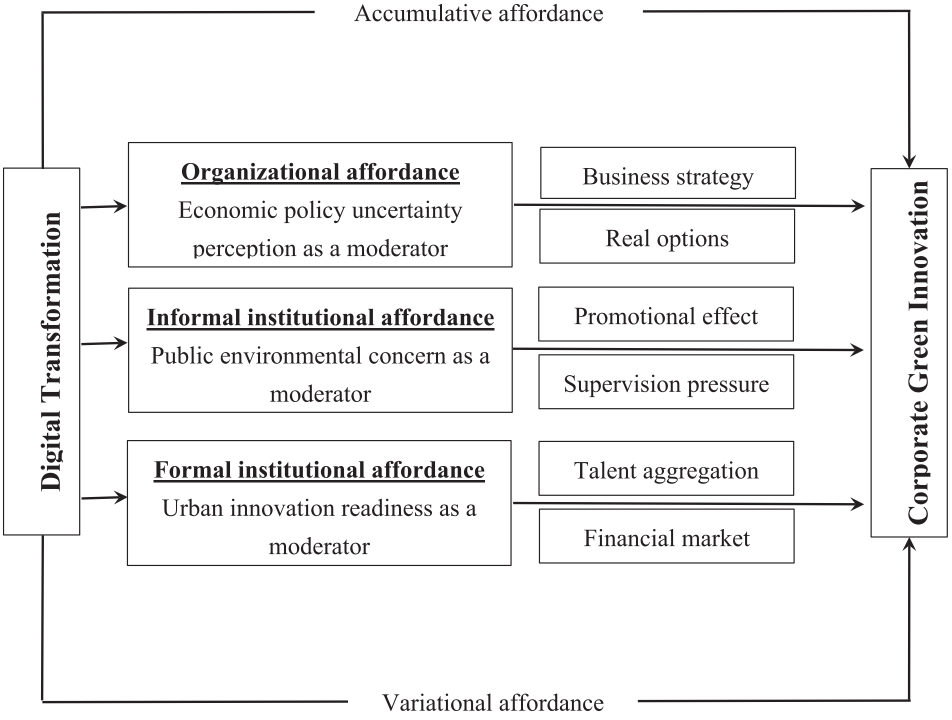

FIGURE 1 Theoretical framework.

3 | DATA AND METHODOLOGY

3.1 | Choice of method

The article adopted the fixed effects regression model as its choice of method to analyze the effect of DT on CGI. The choice of the method was based on several benefits that the fixed effects regression model offers. Fixed effects models effectively control for (unobserved) heterogeneity across firms by mitigating concerns and controlling for time-invariant characteristics (Wooldridge et al., 2016). One major challenge in estimating the relationship between DT and CGI could be the endogeneity problem, with more innovative firms naturally adopting more of DT, leading to reverse causality. The fixed effects model reduces this bias by focusing on within-firm variation over time rather than cross-sectional differences between firms (Baltagi, 2021). Further, previous research has shown the suitability of the fixed effects model for panel data analysis (Baltagi, 2021).

So, for the execution of the fixed effects regression model, we followed several steps as part of the coding process. We began with the variable construction step wherein independent, dependent, and moderating variables were constructed. The variable construction or the choice of variables has been listed in section 3.2 in detail. This was followed by the sample and data screening step, also known as data preprocessing, and is listed in section 3.3. This is followed by the model specification step, wherein the model is built and executed to extract the results. The model specification is detailed in section 3.4. As the final step, the baseline regression was performed by incorporating moderating variables and checking for various robustness with results listed in section 4.

3.2 | Variables construction

3.2.1 | Independent variable

DT is a crucial strategic shift that encompasses the evolution of a firm's user value orientation, intellectual capital value enhancement, corporate governance structure reform, and internal management changes such as organizational structure and marketing models (Li, 2022). These transformations are often challenging to quantify using financial metrics. At the macro level, existing research often relies on industry- or region-level digital economic indicators to measure the progress of digital development. At the micro level, three primary measurement methods are prevalent in existing literature: First, many studies use text analysis to calculate the frequency or proportion of digital-related keywords in annual reports of listed firms to depict the degree of transformation (Li, 2022; Song et al., 2024; Tang et al., 2023); Second, the degree of digital application in a firm is evaluated through questionnaire surveys (Li, Zhou, et al., 2023). This article adopts the first method, referring to Zhang and Guo (2022), to compile the frequency of DT-related terms in listed firms' annual reports. The rationale behind this choice is that keywords related to DT showcase pivotal aspects of firm growth. Firms voluntarily disclose such information in their annual reports to cultivate favor in the capital market and facilitate fundraising endeavors. This article employed a logarithmic processing technique to derive an overarching index denoting the frequency of digital transformation (*FDT*) to mitigate potential biases, particularly the right-skewed bias inherent in such datasets.

3.2.2 | Dependent variable

China Research Data Services Platform (CNRDS) provides information on firms' patent applications and approvals, which are classified according to the "International Patent Classification Green List." Green patent applications offer a glimpse into a firm's commitment to innovation. This article adopts the methodology of Hou et al. (2022) to construct a patent index by taking the natural logarithm of the number of green invention patent applications plus one as a measure of CGI (*GPAT*). Moreover, in additional robustness checks, we substitute the dependent variable with the number of green patent approvals to validate the robustness of the baseline regression results.

3.2.3 | Moderating variables

First, following the approach of Wang et al. (2023), economic policy uncertainty perception (EPU) is constructed using keywords extracted from annual reports of listed firms through Python web scraping technology and Jieba word segmentation software. A higher value indicates a higher perceived economic policy uncertainty by a firm. Second, building on existing research (Gu et al., 2021; Tao et al., 2023), we used an Internet search index for specific environmental keywords to develop a proxy variable for public environmental concern (*PEC*). Internet search data captures market participants' attention to specific events, reflecting their behavioral intentions and preferences. Since the Baidu search engine holds nearly 70% of the market share, the average daily Baidu Index for searches related to these keywords is used to construct PEC for each listed firm. Third, research on regional resilience and innovation has often applied innovation metrics like patent counts, R&D spending, and the number of processes developed as indicators of regional readiness (Pan et al., 2020; Viana et al., 2023; Zheng & Zhang, 2023), allowing for quantification of regions' capacity to support and sustain innovation. Following Pan et al. (2020), this study uses the logarithm of the number of patent applications in a city to represent regional innovation readiness (RIR).

3.2.4 | Control variables

Besides the core variables, this article considers a range of firm-level and city-level factors that may influence CGI (Hou et al., 2022; Pan et al., 2020, 2018). The selected control variables include firm size, debt-to-asset ratio, cash flow, profitability, growth potential, firm age, square of firm age, audit opinion, industry concentration, and regional economic development level.

Table 1 presents the measurement of all variables in this study.

TABLE 1 Main variables.

Variable	Abbreviation	Measurement
Dependent variable		
Corporate green innovation	*GPAT*	ln (number of green invention patent applications + 1)
Independent variable		
Digital transformation	*FDT*	The frequency or percentage of keywords related to digitalization in the annual report of a firm
Moderating variables		
Economic policy uncertainty perception	*EPU*	Keywords extracted from annual reports of listed firms through python web scraping technology and Jieba word segmentation software
Public environmental concern	*PEC*	The average daily Baidu Index for searches related to environmental keywords
Regional innovation readiness	*RIR*	ln (number of patent applications in a city)
Control variables		
Firm size	*size*	ln (total assets at the end of a year + 1)
Debt-to-asset ratio	*loar*	Total liabilities divided by total assets
Cash flow	*cash*	Net cash flow from operating activities divided by total assets
Firm age	*age*	ln (number of years since the firm was established + 1)
Square of firm age	*age*2	[ln (number of years since the firm was established + 1)]2
Industrial concentration	*hhi*	Herfindahl–Hirschman index
Growth potential	*tobin*	Market capitalization divided by total assets
Profitability	*roa*	Net profit after tax divided by total assets
Audit opinion	*oa*	A dummy variable, assigned "1" if there is a reserved opinion, otherwise "0"
Regional economic development	*pgdp*	GDP growth rate of a given year in the province where a firm is registered

TABLE 2 Descriptive statistics.

Variable	N	Mean	SD	Min	Median	Max	P25	P75
GPAT	4,908	0.760	1.081	0.000	0.000	6.900	0.000	1.386
FDT	4,908	1.162	1.253	0.000	0.693	6.216	0.000	1.946
Size	4,908	22.197	1.342	14.942	22.010	28.636	21.271	22.929
Loar	4,908	0.430	1.094	−0.195	0.403	178.345	0.248	0.565
Cash	4,908	0.046	0.101	−10.216	0.047	2.222	0.009	0.087
Age	4,908	2.892	0.338	1.099	2.944	4.159	2.708	3.135
age2	4,908	8.478	1.877	1.207	8.670	17.296	7.334	9.831
Hhi	4,908	0.215	0.205	0.023	0.145	1.000	0.088	0.256
Tobin	4,908	2.243	6.517	0.625	1.637	729.629	1.254	2.358
Oa	4,908	0.960	0.195	0.000	1.000	1.000	1.000	1.000
Roa	4,908	0.030	0.728	−48.316	0.037	108.366	0.013	0.068
Pgdp	4,908	11.293	0.446	10.003	11.310	12.156	10.974	11.613

3.3 | Sample and data screening

The rapid growth of China's digital economy and the swift adoption of digital technology have revealed significant trends since 2012. This study examines A-share listed firms from 2013 to 2022. Financial data of these firms are obtained from the China Stock Market and Accounting Research (CSMAR) database. Patent data is cross-referenced using the CSMAR database and CNRDS. Regional-level data are sourced from the China City Statistical Yearbook.

The article performed the following preliminary screening of the data: (1) excluding special treatment (ST), *ST, and delisted firm samples; (2) excluding financial firms; (3) excluding firm samples with excessive missing information or abnormal data; (4) conducting 1% two-tailed winsorization on continuous variables to eliminate the interference of extreme values on empirical analysis. Ultimately, 33,040 observations from 4,908 listed firms are obtained.

3.4 | Model specification

To assess the impact of DT on CGI in firms, this paper employs a fixed effects regression model for estimation:

$$GPAT_{i,t} = \beta_0 + \beta_1 FDT_{i,t} + \gamma X_{i,t} + \theta_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

where $GPAT_{i,t}$ represents the CGI of firm i in year t, $FDT_{i,t}$ is the core independent variable of this paper, measuring the level of DT of firm i in year t. $X_{i,t}$ denotes control variables, θ_i represents firm fixed effects, μ_t represents year fixed effects, and $\varepsilon_{i,t}$ represents the error term. The coefficient β_1 reflects the relationship between DT and CGI in firms. If the estimated value of β_1 is significantly positive, it indicates that CGI increases as the level of DT rises.

4 | RESULTS

4.1 | Descriptive statistics

Table 2 presents descriptive statistics. The mean of CGI (*GPAT*) is 0.760, with minimum and maximum values of 0 and 6.900, respectively, indicating significant differences in the level of CGI among different firms. The mean of digital transformation is 1.162, suggesting that, on average, 1.162% of the vocabulary in the MD&A section of listed firms' annual reports is related to digitalization, with a maximum value of 6.216. This implies that the MD&A section of annual reports can have up to 6.216% of the vocabulary related to digitalization, showing variations in the emphasis and measures taken for DT among different firms. The distribution characteristics of other variables are similar to those of previous studies.

4.2 | Benchmark regression results

Table 3 presents the baseline regression results of the impact of DT on CGI. The first column of Table 3 shows the regression results with only the core independent variables included. The estimated coefficient value of the independent variable *FDT* is 0.0462, indicating a significant positive effect of DT on CGI at a 1% significance level. For every one percentage point increase in the degree of DT, the level of CGI is expected to increase by 0.0462. Columns (2), (3), (4), and (5) in Table 3 display the regression results after gradually including control variables. The data shows that the estimated coefficients of *FDT* are all positively significant at the 1% level. This suggests that the higher the level of DT in a firm, the more conducive it is to CGI, strongly confirming hypothesis 1. The accumulative and variational affordances of digital technologies enable the homogenization, recombination, programming, and transformation of existing information related to green environmental protection and low-carbon energy efficiency, facilitating firms to achieve targeted and breakthrough CGIs.

TABLE 3 Benchmark regression results.

Variable	(1) GPAT	(2) GPAT	(3) GPAT	(4) GPAT	(5) GPAT
FDT	0.0462***	0.0252***	0.0255***	0.0254***	0.0251***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Size		0.2433***	0.2577***	0.2558***	0.2551***
		(0.020)	(0.020)	(0.021)	(0.020)
Loar		−0.0027	0.0065	−0.0057	−0.0051
		(0.003)	(0.006)	(0.008)	(0.008)
Cash		0.0672	0.1000*	0.0264	0.0273
		(0.045)	(0.051)	(0.045)	(0.046)
Age		2.0137***	1.9795***	1.9662**	1.9783**
		(0.752)	(0.768)	(0.769)	(0.769)
age2		−0.6112***	−0.6100***	−0.6034***	−0.6066***
		(0.228)	(0.232)	(0.232)	(0.233)
Hhi			−0.0152	−0.0133	−0.0139
			(0.048)	(0.048)	(0.048)
Tobin			0.0028***	0.0030***	0.0030***
			(0.000)	(0.001)	(0.001)
Oa				0.0469*	0.0449*
				(0.025)	(0.025)
Roa				−0.0158***	−0.0154***
				(0.005)	(0.005)
Pgdp					0.1497
					(0.148)
Constant	0.7143***	−5.3369***	−5.5688***	−5.5803***	−7.2529***
Observations	27,671	27,665	26,576	26,576	26,570
R-squared	0.7728	0.7799	0.7841	0.7841	0.7839
Id/year fe	Yes	Yes	Yes	Yes	Yes

Note: The t-statistic adjusted for firm-level clustering is shown by the numbers in parenthesis. Significance is indicated at the 1%, 5%, and 10% levels, respectively, by ***, **, and *.

4.3 | Robustness tests

4.3.1 | Endogeneity test

Despite controlling for a wide range of variables in the model, there may still be omitted variables causing endogeneity issues. Meanwhile, the higher the level of CGI, the more likely firms are to take measures to achieve DT, implying that CGI may be the cause rather than the result of DT. To address omitted variables and the impact of reverse causality on the regression results, this study follows the approach of Campello and Gao (2017) by using industry mean as an instrumental variable (IV). The industry mean represents the average level of DT of all firms in the same industry. Due to the similar industry competition environment and technological relationships faced by peer firms, the average level of DT within the industry can represent the degree of DT faced by similar firms to some extent. However, it will not directly affect the DT of the focal firm. The two-stage least squares (2SLS) method is applied to test the endogeneity issue of the model. Table 4 reports the results using the IV-2SLS method. In the first-stage regression, the coefficient of IV (*FDT_IV*) is significantly positive at the 1% level, indicating that a higher level of digitalization in the industry can promote corporate DT. In the second-stage regression, the coefficient of *FDT* is 0.1608, significantly positive at the 1% level. Compared to the baseline regression results, the coefficient value increases, suggesting that after considering endogeneity, the effect of DT on CGI becomes more pronounced. Furthermore, the IV passes weak instrument identification and relevance tests, confirming the robustness of the results.

4.3.2 | Lagging one and two periods of independent variables

Considering the potential time lag effect of corporate DT (Liu, Liu, & Ren, 2023), this study incorporates the independent variable DT with one and two periods of lag in the regression. The results shown in

TABLE 4 Regression results using IV-2SLS.

Variable	(1) First-stage	(2) Second-stage
FDT		0.1608***
		(0.036)
FDT_IV	0.5573***	
	(0.024)	
Size	0.2021***	0.2285***
	(0.019)	(0.022)
Loar	−0.0107	−0.0050
	(0.009)	(0.008)
Cash	−0.1388**	0.0120
	(0.059)	(0.046)
Age	0.1873	−0.1444
	(0.358)	(0.349)
age2	−0.0906	0.0579
	(0.079)	(0.084)
Hhi	−0.1402***	−0.0072
	(0.052)	(0.050)
Tobin	0.0020**	0.0025***
	(0.001)	(0.000)
Oa	−0.0036	0.0467*
	(0.030)	(0.026)
Roa	−0.0122*	−0.0159***
	(0.006)	(0.005)
Pgdp	0.0211	0.2207*
	(0.099)	(0.129)
Observations	26,570	26,570
R-squared		0.0904
Number of stkcd	3,849	3,849
Id fe	Yes	Yes
Year fe	Yes	Yes
Kleibergen-Paap rk LM	436.6335	
Kleibergen-Paap rk Wald F	550.4195	
Cragg-Donald Wald F	765.3938	

Note: The t-statistic adjusted for firm-level clustering is shown by the numbers in parenthesis. Significance is indicated at the 1%, 5%, and 10% levels, respectively, by ***, **, and *.

Table 5, reveal that the coefficient of DT is significantly positive at the 1% and 5% confidence levels in Columns (1) and (2), respectively, confirming the findings of this study.

4.3.3 | Replacing variables

First, we replaced the dependent variable by measuring it through the number of green patents granted, denoted as *pGPAT*. As illustrated in Table 5, the direction and significance of the regression coefficients align with the baseline regression results, affirming the robustness of the findings. Second, we replaced the independent variables. Referring to Wu et al. (2021), a combination of text analysis and expert scoring categorizes keywords into four dimensions: digital technology applications, internet business models, smart manufacturing, and modern information systems. By replacing the frequency database, *FDT* is substituted with *FDT2*. Columns (3) and (4) of Table 5 present the results after replacing the dependent and independent variables, respectively. The coefficients of *FDT* and *FDT2* are 0.0055 and 0.0155, respectively, both statistically significant at the 5% level, validating the robustness of the conclusions.

4.3.4 | Controlling for city and industry fixed effects

Considering that the degree of DT varies among firms in different cities and industries, we further controlled for industry and city fixed effects on top of year fixed effects. This helps to some extent in mitigating endogeneity issues caused by omitted variables. Column (5) of Table 5 shows that the coefficient of *FDT* is 0.0199. Compared to the baseline regression results, the coefficient value has slightly decreased, but it remains significant at the 5% level, supporting the conclusions of this study.

4.4 | Results of moderation effect

In order to further reveal the mechanism of how DT affects a firm's CGI, this study examines the moderating effects of perceived economic policy uncertainty, public environmental concern, and regional innovation readiness in the relationship between DT and CGI. We constructed the following equation to test the moderating effects of these three variables:

$$GPAT_{i,t} = \beta_0 + \beta_1 FDT_{i,t} + \beta_2 Mod_{i,t} + \beta_3 FDT_{i,t} \times Mod_{i,t} + \gamma X_{i,t} + \theta_i + \mu_t + \varepsilon_{i,t} \tag{2}$$

where $Mod_{i,t}$ represents the moderating variable for firm *i* in year *t*. If β_2 of the interaction term $FDT_{i,t} \times Mod_{i,t}$ is significant, it indicates that perceived economic policy uncertainty, public environmental concern, and regional innovation readiness play moderating roles in the relationship between DT on CGI.

Table 6 presents the results of the moderating effects test. In Column (1) of Table 6, the interaction term coefficient between DT and perceived economic policy uncertainty is −0.1505, significantly negative at the 5% level. This indicates that the increase in firms perceived economic policy uncertainty inhibits the promoting effect of DT on CGI. The rise in economic policy uncertainty perception leads managers to make cautious investment decisions, reduces financial institutions' willingness to lend, makes the returns and cash flows from

TABLE 5 Robustness test results.

Variable	(1) GPAT	(2) GPAT	(3) pGPAT	(4) GPAT	(5) GPAT
FDT			0.0055**		0.0199**
			(0.003)		(0.008)
FDT2				0.0155**	
				(0.007)	
l_FDT	0.0217***				
	(0.008)				
l2_FDT		0.0211**			
		(0.009)			
Size	0.2601***	0.2685***	0.0046	0.2565***	0.2559***
	(0.021)	(0.022)	(0.007)	(0.020)	(0.022)
Loar	0.0015	−0.0076	−0.0072	−0.0049	−0.0086
	(0.017)	(0.009)	(0.005)	(0.008)	(0.021)
Cash	0.0191	0.0201	0.0197	0.0266	0.0201
	(0.047)	(0.047)	(0.019)	(0.046)	(0.053)
Age	2.0817**	1.9577**	0.5472**	1.9460**	2.1652***
	(0.830)	(0.856)	(0.254)	(0.771)	(0.834)
age2	−0.6312**	−0.5951**	−0.1886**	−0.5952**	−0.6972***
	(0.249)	(0.257)	(0.078)	(0.233)	(0.255)
Hhi	−0.0314	−0.0453	−0.0175	−0.0162	−0.0732
	(0.052)	(0.055)	(0.020)	(0.048)	(0.064)
Tobin	0.0032***	0.0032***	−0.0000	0.0031***	0.0025***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Oa	0.0463*	0.0478*	−0.0140	0.0427*	0.0155
	(0.025)	(0.026)	(0.012)	(0.025)	(0.029)
Roa	−0.0038	−0.0151***	−0.0048*	−0.0154***	−0.0099*
	(0.019)	(0.005)	(0.003)	(0.005)	(0.006)
Pgdp	0.1553	0.1595	0.0586	0.1491	0.2767
	(0.146)	(0.149)	(0.073)	(0.149)	(0.212)
Constant	−7.4891***	−7.6425***	−0.6127	−7.2876***	−8.4209***
	(1.797)	(1.833)	(0.884)	(1.821)	(2.511)
Observations	24,706	23,150	26,564	26,570	25,317
R-squared	0.7858	0.7871	0.6670	0.7838	0.8151
Id/year fe	Yes	Yes	Yes	Yes	Yes
Year#ind fe	No	No	No	No	Yes
Year#cityid fe	No	No	No	No	Yes

Note: The t-statistic adjusted for firm-level clustering is shown by the numbers in parenthesis. Significance is indicated at the 1%, 5%, and 10% levels, respectively, by ***, **, and *.

immediate investments uncertain, and results in the CGI falling short of expectations, thereby verifying H2. Moving on to column (2), the interaction term coefficient between DT and public environmental concern is significantly positive at the 5% level, indicating that an increase in public environmental concern further strengthens the promoting effect of DT on CGI. The increase in public environmental concern enhances firms' exposure, promotes the dissemination and disclosure of information, imposes certain monitoring pressure on firms, and encourages firms to actively engage in GI activities during the DT process, thus verifying H3. Lastly, in column (3), the interaction term coefficient between DT and regional innovation readiness is significantly positive at the 10% level, implying that regional innovation readiness can significantly and positively moderate the effect of DT on CGI. This suggests that a higher level of regional innovation

TABLE 6 Regression results of moderating effects.

Variable	(1) GPAT	(2) GPAT	(3) GPAT
FDT	0.0378***	0.0652***	0.0688***
	(0.012)	(0.041)	(0.051)
EPU	−0.0367**		
	(0.088)		
PEC		0.0069*	
		(0.026)	
RIR			0.0848***
			(0.030)
FDT×EPU	−0.1505**		
	(0.076)		
FDT×PEC		0.0175**	
		(0.008)	
FDT×RIR			0.0090*
			(0.005)
Size	0.2681***	0.2648***	0.2656***
	(0.025)	(0.021)	(0.022)
Loar	−0.0156	−0.0135	0.0042
	(0.049)	(0.013)	(0.028)
Cash	0.0606	0.0161	−0.0012
	(0.074)	(0.048)	(0.048)
Age	2.0101**	1.9696**	1.9052**
	(0.971)	(0.785)	(0.806)
age2	−0.6188**	−0.6074**	−0.5917**
	(0.290)	(0.238)	(0.244)
Hhi	−0.0344	−0.0229	−0.0328
	(0.065)	(0.051)	(0.052)
Tobin	0.0135***	0.0031***	0.0031***
	(0.003)	(0.001)	(0.001)
Oa	0.0600**	0.0411	0.0380
	(0.030)	(0.026)	(0.027)
Roa	−0.0717	−0.0159***	0.0042
	(0.050)	(0.005)	(0.019)
Pgdp	0.3036*	0.1500	0.1765
	(0.171)	(0.150)	(0.154)
Constant	−9.2194***	−7.3887***	−8.5609***
	(2.084)	(1.826)	(1.883)
Observations	16,986	25,092	24,147
R-squared	0.8065	0.7867	0.7887
Id/year fe	Yes	Yes	Yes

Note: The t-statistic adjusted for firm-level clustering is shown by the numbers in parenthesis. Significance is indicated at the 1%, 5%, and 10% levels, respectively, by ***, **, and *.

readiness strengthens the talent agglomeration effect, improves the financial market's efficiency, and creates a more favorable environment for firms to engage in GI, fully confirming H4.

4.5 | Heterogeneity analysis

4.5.1 | Firm ownership

Ownership of firms plays a crucial role in resource allocation, data utilization, and other production factors. Firms with different ownership types exhibit variations in their emphasis on and actions toward CGI (Pan et al., 2020). The regression results are displayed in Columns (1) and (2) of Table 7 by categorizing SOEs and non-SOEs based on ownership structures and capital sources. In the analysis of SOEs, DT demonstrates a significant promoting effect on CGI. Conversely, in the non-SOE analysis, the key independent variable FDT coefficient is positive but lacks statistical significance. Compared to their non-state-owned counterparts, SOEs possess established production technologies and robust industrial foundations, allowing them to offer sufficient financial and technological backing for CGI initiatives. Moreover, SOEs undertake more social responsibilities, actively comply with national digital economic regulations, and implement corresponding strategies, resulting in more pronounced effects.

4.5.2 | Production factor intensity

The sample is categorized into three groups based on production factor intensity: labor-intensive, capital-intensive, and technology-intensive (Han et al., 2022). The regression results for these groups are presented in Columns (3), (4), and (5) of Table 7. The results reveal that DT has a notable positive effect on CGI in labor-intensive firms, as evidenced by the statistically significant coefficient of the independent variable *FDT* at the 1% significance level. Conversely, this impact is insignificant for capital-intensive and technology-intensive firms. The rationale behind this discrepancy lies in the cost pressures faced by labor-intensive firms, such as escalating labor costs under traditional production methods, which incentivize them to pursue CGI for cost reduction and efficiency improvement. Utilizing software, technology, and patents during the DT process aligns with the operational needs of labor-intensive firms, thereby propelling CGI. In contrast, capital-intensive firms have traditionally accumulated more tangible assets. At the same time, GI predominantly hinges on intangible asset accumulation, explaining the relatively weaker influence of DT on fostering CGI in these entities. Likewise, technology-intensive firms, already exhibiting high levels of CGI internally, may not experience substantial effects from DT.

5 | DISCUSSION AND CONCLUSION

This study delves into the relationship between DT and CGI, utilizing data from publicly listed firms from 2013 to 2022 through affordance theory. While analyzing RQ1 through hypothesis H1, our findings affirm that DT significantly enables CGI by capitalizing accumulative and variational affordances. This implies that, by leveraging DT, firms can optimize processes and energy use, reduce waste, and minimize

TABLE 7 Regression results of heterogeneous analysis.

Variable	(1) State-owned *GPAT*	(2) Non-state-owned *GPAT*	(3) Labor intensive *GPAT*	(4) Capital intensive *GPAT*	(5) Technology intensive *GPAT*
FDT	0.0647***	0.0083	0.0269***	0.0062	0.0083
	(0.015)	(0.009)	(0.008)	(0.031)	(0.022)
Size	0.3154***	0.2363***	0.2535***	0.4107***	0.2072***
	(0.042)	(0.024)	(0.024)	(0.091)	(0.042)
Loar	−0.0586	0.0101	0.0003	−0.0096	0.0561
	(0.099)	(0.016)	(0.007)	(0.071)	(0.061)
Cash	−0.1175	0.0153	0.0426	−0.1827	0.2447*
	(0.086)	(0.060)	(0.052)	(0.125)	(0.146)
Age	0.4989	1.9065**	1.4049	0.0273	5.6563**
	(1.294)	(0.943)	(0.854)	(1.440)	(2.819)
age2	−0.1783	−0.4956*	−0.4130	−0.0812	−1.8128**
	(0.391)	(0.288)	(0.259)	(0.521)	(0.835)
Hhi	−0.0592	0.0052	−0.0883	0.1604	0.3132**
	(0.091)	(0.060)	(0.055)	(0.160)	(0.140)
Tobin	0.0086	0.0027***	0.0026***	0.0242***	0.0129***
	(0.006)	(0.001)	(0.000)	(0.008)	(0.004)
Oa	0.0223	0.0432	0.0307	0.1056	0.0860
	(0.060)	(0.030)	(0.027)	(0.138)	(0.070)
Roa	−0.1453*	0.0039	−0.0150***	0.0074	0.0982
	(0.083)	(0.018)	(0.005)	(0.060)	(0.085)
Pgdp	0.4691*	−0.1314	0.1167	0.1281	0.4191**
	(0.280)	(0.126)	(0.200)	(0.301)	(0.197)
Constant	−11.4369***	−4.4539***	−6.7977***	−9.5101**	−10.0284***
	(3.475)	(1.588)	(2.391)	(4.268)	(3.116)
Observations	8,718	17,141	21,212	2,087	3,143
R-squared	0.8305	0.7414	0.7815	0.7627	0.8192
Id/year fe	Yes	Yes	Yes	Yes	Yes

Note: The t-statistic adjusted for firm-level clustering is shown by the numbers in parenthesis. Significance is indicated at the 1%, 5%, and 10% levels, respectively, by ***, **, and *.

their carbon footprint (Gao, Cheng, & Sun, 2023). This is consistent with the previous studies that highlight the role of DT in enhancing resource efficiency and green innovation (Gao, Xu, & Zhou, 2023; Liu et al., 2024; Xie & Qi, 2024). Further, DT's accumulative and variational affordances create opportunities for firms to implement green innovation strategies resonating with affordance theory applied in the digital transformation context (Liu, Mao, et al., 2023; Szűcs-Luipold, 2024).

While addressing RQ2 through hypotheses H2, H3, and H4, the public environmental concern, economic policy uncertainty, and regional innovation readiness significantly moderate the relationship between DT and CGI. Public environmental concern amplifies this relationship, supporting firms in aligning their DT with sustainability goals and CGI, as supported by Kuokkanen and Sun (2020) and Litvinenko et al. (2020). On the other hand, economic policy uncertainty weakens the relationship between DT and CGI, with firms adopting risk-averse strategies that stifle innovation, echoing the findings of Baker et al. (2022) and Gulen and Ion (2016). Further, regional innovative readiness positively moderates the relationship by providing the necessary infrastructure, process improvement, or introduction of new processes through patents, talent, and regulatory support, which is essential for supporting CGI. This is in sync with the studies of Guzman et al. (2024) and Pidorycheva et al. (2020), who emphasized the importance of regional ecosystems for fostering innovation. In addition, heterogeneity analyses show that the impact of DT on CGI is more pronounced in SOEs and labor-intensive firms.

In conclusion, the research bridges gaps in understanding how green innovation can be optimized through digital transformation across various institutional contexts, contributing to academia and industry.

6 | IMPLICATIONS

6.1 | Theoretical implications

This research provides significant theoretical contributions. First, this paper contributes to the literature on the relationship between DT and CGI. Previous literature has adopted traditional frameworks such as resource allocation, dynamic capabilities, and innovation diffusion to elucidate the DT-CGI relationship (Ghobakhloo et al., 2021; Hanelt et al., 2021; Mariani et al., 2023). By introducing affordance theory, this study offers a fresh perspective on the dynamics between DT and CGI. By doing so, it moves away from traditional frameworks, shedding light on the nuanced interplay between digital technology and green initiatives. Hence, it advances the application of affordance theory in organizational and innovation studies.

Second, this research contributes to institutional affordance by emphasizing the multifaceted nature of affordances. By delving into the mechanisms of economic policy uncertainty perception, public environmental concern, and regional innovation readiness in the relationship between DT and CGI, the research uncovers complex interactions among technological affordance, organizational affordance, and formal and informal institutional affordances. This approach enriches the understanding of how formal and informal institutions shape corporate behavior that supports DT, leading to sustainable outcomes. This emphasis signifies a paradigm shift toward a holistic view that recognizes the interconnectedness of technology, organizations, and institutions in shaping the potential uses of digital technologies.

Third, this research deepens our understanding of how digital technology influences CGI across different sectors and ownership structures. By recognizing the importance of sector nuances and ownership landscapes in tailoring effective strategies for integrating digital technologies into CGI, this study provides valuable insights into this intricate relationship within diverse organizational contexts.

6.2 | Policy implications

The findings of this research provide important practical and policy implications. First, recognizing public concern's external supervision and incentive role is crucial for firms undergoing DT. Firms should actively engage with stakeholders, including the public, to address concerns about environmental impact, among other issues. Firms have a responsibility not only to their shareholders but also to society at large. This includes minimizing their environmental footprint and contributing positively to the communities in which they operate. By recognizing the importance of public concern in shaping their actions, firms can align their strategies with broader social goals, fostering sustainable development.

Second, the policymakers must ensure coherence and unity in their economic policies to reduce uncertainty. Policymakers should aim to reduce uncertainty by ensuring a stable and predictable regulatory environment. Such stability would motivate firms to invest in long-term green innovation initiatives without abrupt policy changes that can cost them. Additionally, there should be a focus on enhancing policy continuity, especially during times of economic downturn. Increasing the clarity of policy interpretation is crucial to avoid misunderstandings and boost market expectations. Positive and stable policy expectations are necessary to attract stable investments and talents for firms, increase R&D investment, minimize external resistance, and foster CGI within firms.

Third, policymakers should invest in infrastructure, talent development, and innovation networks that enable firms to leverage DT to make firms fully green. By fostering public-private partnerships, offering financial incentives, and creating innovation clusters, the government can enhance regional innovation readiness and facilitate the integration of green innovation into digital transformation strategies.

Fourth, for firms struggling with DT, policymakers should consider offering environmental subsidies, loan discounts, and other forms of support to ease the transition and encourage CGI. In terms of new infrastructure development, emphasis should be placed on rapidly deploying information network facilities to create a robust digital infrastructure. For example, building an integrated digital platform can enhance R&D capabilities for digital technology infrastructure; promoting collaboration along the industrial chain can facilitate the seamless integration of the digital economy with the real economy. By enabling firms to leverage these resources effectively, the policymakers can drive significant progress in CGI.

6.3 | Limitations and directions for future research

The study provides various insights for academicians and policymakers but is not devoid of shortcomings. Several limitations and potential directions for future research may and should be considered.

First, the study is limited to the specific geographical region, China, which may limit the generalizability of the results to the other areas. Future research may benefit by expanding the research horizon to different geographical regions to understand the regional variations, thus adding to the generalizability of the results. Cross-country comparative studies could provide valuable insights into how DT affects CGI in different institutional and market environments. Second, the study may not fully address the corporate landscape as the sample is limited to A-shared listed firms. Future research could expand the sample to incorporate more diverse firm types. Third, the study may not account for differences in DT and CGI across different industries other than what has been discussed in the paper. In future research, exploring industry-specific characteristics can help to understand how digital transformation influences green innovation differently across industries, and offer tailored strategies for promoting sustainability. Fourth, the constructs used in the current study are not exhaustive and may have omitted potential variables like corporate culture or leadership roles. While this study examines the moderating effects of three variables on DT and CGI, future research may consider including other variables like leadership and corporate culture, which are other important moderating variables that may not be considered. In addition, researchers may consider exploring a mixedmethod approach to better understand the complex interplay between DT and CGI, simultaneously describing statistical and contextual shades.

CONFLICT OF INTEREST STATEMENT

The author(s) declare no conflict of interest with respect to the research, authorship, and/or publication of this article.

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