6 Digital Transformation and Green Innovation Efficiency in Heavy-Polluting Enterprises: A Focus on Knowledge and Slack Resources

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Abstract

This study aims to assess the impact of digital transformation (DT) on the green innovation efficiency of heavy-polluting enterprises (HEGIE), employing the Super-SBM model as the core methodology. Using panel data spanning from 2012 to 2022, this study investigates the relationship between DT and HEGIE and its underlying mechanisms. The findings reveal a positive relationship between DT and HEGIE, highlighting DT as a catalyst for enhancing environmental sustainability within these enterprises. Heterogeneity analysis implies that firms in the growth and maturity stages and firms located in the East and Central regions are more likely to benefit from DT in terms of green innovation efficiency. Mechanism analysis reveals that DT boosts HEGIE by facilitating the acquisition of knowledge resources, increasing high discretion slack resources while reducing low discretion slack resources. This study provides empirical evidence for understanding how DT contributes to green innovation capabilities from the perspectives of knowledge capital optimization and resource allocation, which inspires heavy-polluting enterprises to focus on maximizing the benefits from DT measures, thereby empowering their goal toward achieving green transformation.

Keywords: Digital Transformation; Green Innovation Efficiency; Super-SBM Model; Heavy-polluting Enterprises; Knowledge Resources; Slack Resources

JEL Classification: Q55; M15;O30

1. Introduction

China has currently entered the mid-to-late industrialization stage of economic development (Kong *et al.*, 2022). An urgent need exists to transition from high-speed growth to a high-quality, green efficiency-driven model of modernization(Wu, Ma and Tang, 2019). However, the long-term solidification of the extensive growth model has caused high energy-consuming and heavy-polluting industries, such as iron and steel, cement and metallurgy, to occupy an important part

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in China's industrial structure(Y. Li *et al.*, 2021), which poses a serious threat to the green sustainable development of the Chinese economy(Zhu et al., 2019). The Chinese government has increasingly acknowledged that heavy-polluting enterprises can no longer rely on simple innovation transformation(Hu *et al.*, 2021), nor remain confined to a phase of governance that focuses on the end environment performance(Ran *et al.*, 2023). Promoting green transformation is the critical pathway to addressing this practical dilemma, which has also been proven by relative environment governance studies(Mao, Wang and Sun, 2019; Tian *et al.*, 2022).

In recent years, the comprehensive perspective of Green Innovation Efficiency (GIE) has drawn extensive academic attention as an effective criterion for evaluating green transformation performance. It helps to discern whether green innovation is a substantive response or merely a strategy for the sake of legitimacy (Luo and Zhang, 2021; He, Ribeiro-Navarrete and Botella-Carrubi, 2023). Significantly improving the green innovation efficiency (HEGIE) of heavy-polluting enterprises is essential to harmonize the economy and the environment, and thus to promote high-quality growth in the Chinese economy(Wang, Tang and Choi, 2021). However, it is undeniable that China's HEGIE is still not at the desired level and challenges remain. In many cases, green innovation is driven by environmental regulations, but the effectiveness of these external regulations is often constrained by the intricate policy implementation. This approach may not be the best solution to all environmental issues(Tang, Qiu and Zhou, 2020). Furthermore, the limited green technology R&D capacity is also a significant barrier to green innovation transformation (Song *et al.*, 2020). These practical dilemmas make heavy-polluting enterprises seek a new survival path from the inside.

Practical experience and theoretical research reveal that the essential approach to solving environmental pollution concerns is to innovate technology and models(Wei and Zhou, 2023). The digital economy in the context of Industrial Revolution 4.0 is a typical transformative socio-technical paradigm. With the comprehensive application of digital technologies such as big data, artificial intelligence, and blockchain, digitization has the potential to optimize resource allocation and promote the low-carbon transformation of the entire chain of traditional industries, which undoubtedly brings new opportunities to enhance HEGIE(He, Du and Tu, 2023). Therefore, it has become urgent to study whether DT can enhance HEGIE.

Most scholars have supported the beneficial contribution of DT to green development and environmental performance(Chen and Hao, 2022; Guo, Geng and Yao, 2022). While these studies provide valuable inspiration for our research puzzle, there are still unresolved concerns here. First, there is few specialized surveys on heavy-polluting industries. Given the important role of these industries in the national economy, they cannot be ignored (Hu *et al.*, 2021). As the largest developing country facing the challenge of high-quality development, China's heavy-polluting enterprises are the ideal micro-experimental object that deserves more attention. Second, existing research on the impact of DT on HEGIE has yielded mixed results(Wen, Lee and Song, 2021), with scholars mostly revealing the transmission channels from the perspectives of financing constraints and strengthened supervision, but the impact mechanism still belongs to a "black box", and there is an urgent need for new research perspectives to gain a broader understanding of the greening effect of the DT. Therefore, the research objectives of this article include, first, constructing a system of HEGIE measures and assessing its performance, and second, testing the effect of DT on HEGIE and exploring the mechanisms from the perspectives of knowledge resources and redundant resources. Specifically, based on the panel data of heavy-polluting listed enterprises in China from 2012 to 2022, this article employs the Super-SBM model and text-mining methods to quantify HEGIE and DT and test their relationships, respectively.

This article contributes to related literature in several important ways. Firstly, taking the micro heavy-polluting enterprise as the research object, this article adds green invention patents to the measurement system to calculate the HEGIE. Unlike most previous studies that only included economic benefits in expected output, the calculation method of this article highlights the concept of green and optimizes the traditional GIE measurement. Secondly, in contrast to previous studies that have mainly examined the macro-level benefits of digital technologies(Zhao and Fang, 2023), our investigation shifts to a micro perspective, focusing on enterprises in specific industries, and reveals the positive impact of DT on high environmental green innovation efficiency HEGIE, thus enriching and broadening the discussion on the micro-level green dividends of the digitalization paradigm. Thirdly, the study provides insights into the complex mechanisms through which DT impacts HEGIE. While previous studies have mostly explored the mechanisms from the perspectives of financing constraints and innovation cooperation networks(Tang *et al.*, 2023), this article analyzes how DT facilitates the flow and expansion of knowledge and optimizes the allocation of idle resources from the perspectives of the acquisition of intellectual capital and the management of slack resources, makes a timely and substantive contribution to the existing literature.

2. Theoretical Framework and Research Hypothesis

2.1 Direct Influence of DT on HEGIE

The DT of heavy-polluting enterprises is reflected in the application of modern digital information elements in the entire production process(Verhoef *et al.*, 2021). At the input end, according to the endogenous growth theory, DT has advantages such as improving innovation capabilities, optimizing human capital structure, and reducing financing constraints(Xue *et al.*, 2022). Digitization can also bring flexibility and fast response, which greatly optimizes the efficiency of resource allocation(Wu, Shi and Wang, 2023). It will facilitate the collection, storage, and analysis of information in the value chain by heavy-polluting enterprises, and achieve intelligent production(Lee, Yuan and Wang, 2022). On the output side, some scholars believe that DT promotes the embedding of digital technology, and shows a technology spillover effect. It contributes to green technology research and development(Wen, Zhong and Lee, 2022), and reduces carbon emission performance, which brings relatively considerable economic and environmental returns for enterprises(Zhai, Yang and Chan, 2022).

Therefore, this article proposes the first hypothesis:

H1: DT has a positive effect on HEGIE.

2.2 Indirect Influence of DT on HEGIE

Against the backdrop of heightened global concern for environmental protection and sustainable development, heavy-polluting enterprises not only have to meet increasingly stringent environmental regulations, but also must maintain innovative competitiveness in market competition. As a new technological tool, DT is becoming an important way for heavy-polluting enterprises to enhance the efficiency of green innovation. For heavy-polluting enterprises, it not only means the renewal of technology and equipment, but also the reintegration and optimization of knowledge resources within the enterprise. These knowledge resources are the core elements of enterprise innovation activities. DT, through the integration of information systems and the extensive collection and analysis of data, can significantly enhance the knowledge resources of enterprises(McPhillips and Licznerska, 2021), which in turn provides power for HEGIE. Specifically, according to the open innovation theory(Chesbrough, 2003) and innovation diffusion theory(Walker, 1969), this process involves two specific aspects, including the increase of knowledge flow and the expansion of knowledge width. First, the knowledge flow directly affects the HEGIE. DT can significantly facilitate the flow of green knowledge in enterprises by building efficient information systems and collaboration platforms. For example, through digital collaboration with external research institutions and partners, enterprises can access the latest green technology and market information, thus accelerating the innovation process(Wang and Zhang, 2023). Secondly, enterprise knowledge width refers to the breadth and diversity of knowledge that an enterprise possesses. The wider the breadth of knowledge, the more flexible an enterprise can be in responding and innovating in the face of a complex and changing market environment(J. Li *et al.*, 2021). DT, through technologies such as big data analytics and artificial intelligence, can help enterprises broaden their knowledge base by collecting and analyzing information from a wide range of different fields and sources y(Lee and Chen, 2020). For example, by analyzing data from different markets and technological fields, enterprises can discover new green technologies and business models, thus enhancing their green innovation efficiency.

Based on the above analysis, this article proposes the hypothesis:

H2: DT promotes HEGIE by optimizing the allocation of knowledge resources.

H2a: DT improves HEGIE by increasing knowledge flows.

H2b: DT improves HEGIE by increasing knowledge width.

According to the resource-based view and resource dependence theory, green innovation in heavy-polluting enterprises usually relies on substantial resource investment (Meng *et al.*, 2016). The allocation and management efficiency of these resources are directly linked to the firm's innovation potential. The concept of redundant resources was first proposed by March & Simon (1958), also known as organizational slack in early literature(Bourgeois, 1981), refers to the cushion of actual or potential resources that enables an organization to respond to the demands of internal adjustment or external pressure for policy change. Sharfman et al. (1988) further distinguished between high-discretion and low-discretion slack resources, highlighting their differentiated impacts on firm development. According to the principal-agent theory, the low discretion slack is mostly residual resources in business activities, such as idle equipment, which will crowd out innovation resources, leading to rigid enterprise behavior, and curbing green innovation(Tan and Peng, 2003). Conversely, high discretion slack resources, like cash and raw materials inventory, offer greater flexibility and autonomy to managers, facilitating knowledge learning and sharing, thereby enhancing green innovation efficiency(Wang, Shen and Ngai, 2023). Heavy-polluting enterprises engaged in DT tend to have advantages in resource integration, screening, and adjustment(Tang *et al.*, 2021), particularly through digital technologies that uncover resources and reduce dependency on specific ones (Deperi *et al.*, 2022), thus optimizing resource allocation and driving HEGIE. Therefore, the third hypothesis is proposed as follows:

H3: In the process of DT affecting HEGIE, different slack resources play different mediating roles.

H3a: DT enhances HEGIE by reducing the low discretion slack resources.

H3b: DT enhances HEGIE by increasing high discretion slack resources.

3. Research Strategies

3.1 Sample Selection

This article selects Shanghai and Shenzhen A-shares listed enterprises in heavy-polluting industries from 2012 to 2022 as the main research samples. Appendix A provides the details of the industry code and industry name. To assure the accuracy of the research results, enterprises with special treatment (ST), and special transfer (PT) are excluded. In addition, some of the missing values are interpolated.

3.2 Model Design

$$HEGIE_{k,i,t} = \alpha_0 + \alpha_1 DT_{k,i,t-1} + \sum \varphi CVs + \sum Year + \sum Ind + \sum City + \varepsilon_0 \quad (1)$$

Where, $HEGIE_{k,i,t}$ stands for the efficiency value of the *k* firm in year *t* in the city *i*, $\boldsymbol{DT_{k,i,t-1}}$ represents the lag term of digital transformation degree, $\boldsymbol{\alpha_1}$ is the estimated coefficient of the explained variables, CVs refers to the control variables, $\sum Year$ stands for the time-fixed effect, $\sum Ind$ is the industrial fixed effect, $\sum City$ is the industrial fixed effect, and ε_0 is the random error item.

$$M_{k,i,t} = \alpha_0 + \alpha_1 DT_{k,i,t-1} + \sum \varphi CVs + \sum Year + \sum Ind + \sum City + \varepsilon_0 \quad (2)$$

$$HEGIE_{k,i,t} = \alpha_0 + \alpha_1 DT_{k,i,t-1} + \alpha_2 M_{k,i,t} + \sum \varphi CVs + \sum Year + \sum Ind + \sum City + \varepsilon_0 \quad (3)$$

Models (1)-(3) are employed to explore the transmission mechanism of the effect of DT on HEGIE. $\boldsymbol{M_{k,i,t}}$ stands for the mechanism variables, $\boldsymbol{\alpha_2}$ is the estimated coefficient of the mechanism variables.

3.3 Variables Selection and Data

This article uses the input-output method to calculate HEGIE, as shown in Table 1.

Table 1. Input-Output Indicators for Measuring HEGIE

Types	Indicators	Variables	Unit	Data sources
Input	Labor input	Enterprise personnel	Person	CSMAR database
	Capital investment	R&D expenditure	RMB	
	Energy consumption	Various resources such as water, electricity, coal, etc	Ton of standard coal equivalent	Annual reports and social responsibility reports of listed companies
Output	Desirable output	Operating revenue	RMB	CSMAR database
		Green invention patent	Item	State Intellectual Property Office and Green List of International Patent Classification
	Undesirable output	Exhaust gas emission	Ton of standard coal equivalent	Enterprise operating costs: CSMAR database. Industry operating costs: National Statistical Yearbook. Industry Carbon Emissions: China Energy Statistics Yearbook.

Resource Investment: Referring to some existing literature(Lin and Guan, 2023), this part includes three key elements: human capital, R&D capital, and energy consumption. Particularly, R&D capital is processed using the perpetual inventory method to represent capital stock concepts.

Output Variables: In general, output variables include desirable output and undesirable output. Given that green invention patents represent the major aspect of green innovation capacity and environmental performance(Aghion *et al.*, 2016), green invention patents are seen as one of the most important desirable outputs. Moreover, some scholars suggest that desirable output should show the economic benefits resulting from enterprises' green production activities(Zhang, Rong and Ji, 2019). Therefore, the operational revenue are included. In terms of undesirable output, carbon dioxide emissions are selected as the key indicator (See Appendix B for the calculation). Considering the time-dynamic characteristics of production activities, we employ a lag of one period for all output factors to ensure the accuracy of the research.

Super-SBM Model: To reduce the deviation of the calculation results, this article adopts the improved super-SBM model to evaluate the HEGIE.

Assuming that the sample firms in this study are n DMUs, each firm should have three types of variables, inputs, desired outputs, and undesired outputs, which are represented by $x \in R^m, y^d \in R^{s1}, y^u \in R^{s2}$, respectively, the matrices are as follows:

$$X = [x_1, x_2 \ldots, x_n] \in \mathrm{R}^{m \times n}$$

$$y^d = \left[y_1^d, y_2^d \ldots, y_n^d\right] \in R^{r_1 \times n} \qquad (4)$$

$$y^u = [y_1^u, y_2^u \ldots, y_n^u] \in \mathrm{R}^{r_2 \times n}$$

$$\text{i.e. } X > 0, y^d > 0, y^u > 0$$

The production possibilities set (P) can be defined as:

$$P = \{(x, \quad y^g, \quad y^b) | x \geq X\lambda, \quad y^b = Y^b\lambda, \quad \lambda \geq 0\} \text{ (5)}$$

Thus, the SBM model is shown below:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_j^-}{X_{ik}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{p=1}^{r_1} \frac{s_p^d}{y_{pk}^d} + \sum_{q=1}^{r_2} \frac{s_q^u}{y_{qk}^u}\right)}$$

$$S.t \begin{cases} X_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- \\ y_{pk}^d = \sum_{j=1}^{n} y_{pj}^d\lambda_j - S_p^d \\ y_{qk}^u = \sum_{j=1}^{n} y_{qj}^u\lambda_j + S_q^u \\ \lambda_j > 0, S_i^- \geq 0, S_p^d \geq 0, S_q^u \geq 0 \end{cases} \qquad (6)$$

Where, X_{ik} stands for the i_{th} input value of DMU_k, Y_{pk}^d is the desirable output, Y_{qk}^u is the undesirable output and λ stands for the weighted vector. However, this model does not rank multiple simultaneously efficient DMUs, thus, (Tone, 2002) proposed an improved super-SBM model to solve this problem, which can be stated as follows.

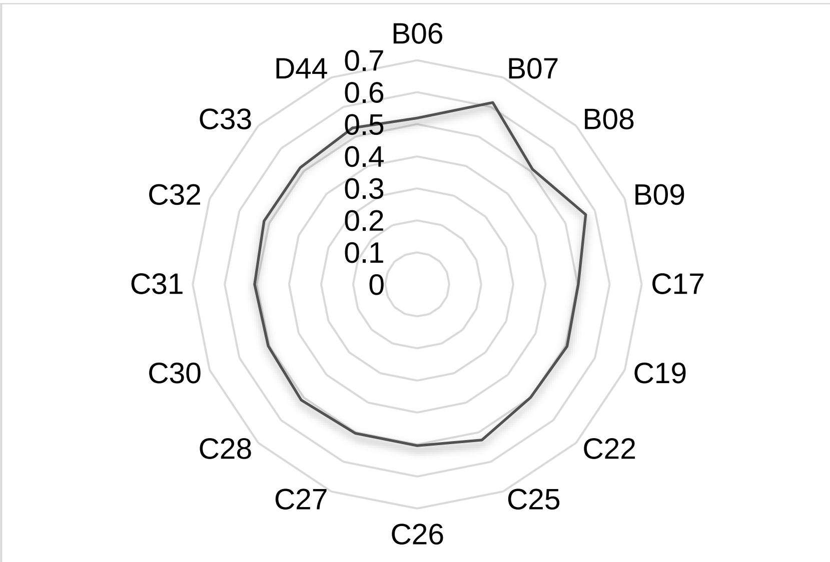
$$\phi^* = min \frac{\frac{1}{m}\sum_{i=1}^{m} \frac{\bar{x}}{X_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{p=1}^{r_1} \frac{\bar{y}^d}{y_{pk}^d} + \sum_{q=1}^{r_2} \frac{\bar{y}^u}{y_{qk}^u}\right)}$$

$$s.t\begin{cases}\bar{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j \\ \bar{y}^d \leq \sum_{j=1,\neq k}^{n} y_{pj}^d\lambda_j \\ \bar{y}^u \geq \sum_{j=1,\neq k}^{n} y_{qj}^u\lambda_j \\ \lambda_j > 0, \bar{x} \geq x_k, \bar{y}^d \leq y_k^d, \bar{y}^u \geq y_k^u \end{cases} \quad (7)$$

Where, ϕ^* represents the efficiency value of the DMU, unlike the traditional SBM model, its value can be greater than 1. $\bar{x}, \bar{y}^d$ and $\bar{y}^u$ are the mean indicators of inputs, desirable output, and undesirable output, respectively.

Figure 1

HEGIE Industry Average Radar Chart

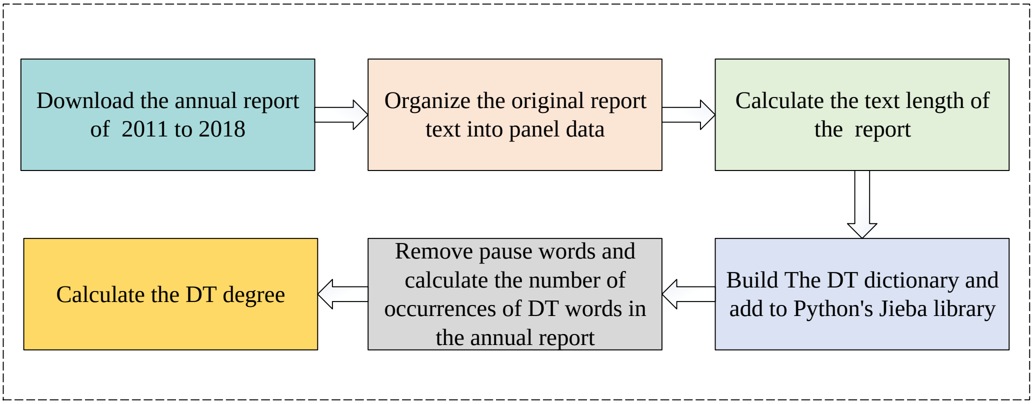


This article uses the MAXDEAUltra9 software to calculate HEGIE. From the perspective of sub-industries, the comparison of average GIE in heavy-polluting industries is shown in Figure 1. The average GIE in the B07(Oil and gas extraction industry) is the highest and the lowest is C22 (Paper and paper products industry). The ranking of the average HEGIE values is B07<B09<D44<C25<B06<C32<C33<C28<B08<C31<C19<C27 <C26 <C30 <C17 <C22.

The measure of DT: In the available literature, text mining is the most common approach for evaluating the DT of enterprises. Referring to other scholars(Wu *et al.*, 2021), this article calculates a DT index for heavy-polluting enterprises. For specific processes, see Figure 2 and Appendix C.

Figure 2

Calculation Steps of Enterprise DT



Control Variables: This study introduces Tobin's Q Ratio (TobinQ), ownership concentration (Lnlargest), duration of enterprise establishment (Age), debt ratio (Lev), and asset-income ratio (ROA) as control variables following Hsieh et al.(2022) and Xu et al. (2023). *TobinQ* is measured by the ratio of the market capitalization to total assets; *Lnlargest* is characterized by the logarithm of the percentage of shares of the first largest shareholder; *Age* is expressed as one plus the difference between the current year and established year; *Lev* is calculated by the ratio of total liabilities to total assets. *ROA* is represented by the ratio of net profit to total assets. These variables are obtained by the CSMAR database.

Descriptive statistics are reported in Table 2. The values of 1/VIF are all close to 1 and there is no covariance between the variables.

Table 2. Descriptive Statistics

Variables	Obs.	Mean	Sd	Min	Max	1/VIF
HEGIE	6,214	0.504	0.023	0.500	0.835	--
DT	6,214	0.553	0.815	0.000	3.367	0.979
Lev	6,214	0.435	0.210	0.055	0.954	0.752
Age	6,214	20.569	5.557	5.000	45.000	0.964
TobinQ	6,214	1.980	1.309	0.818	8.320	0.887
Lnlargest	6,214	3.464	0.465	2.206	4.342	0.934
ROA	6,214	0.037	0.069	-0.273	0.213	0.789

Notes: Obs. represents the research sample numbers. Mean stands for the average value of each variable. Sd stands for the standard deviation. Min and Max represent the minimum and maximum values of each variable, respectively. VIF stands for variance inflation factor.

4. Research Results and Analysis

4.1 Benchmark Regression Results

Table 3 reports the benchmark regression results, corresponding to the core research hypothesis of this article. Among them, column (1) corresponds to the relationship between the DT and HEGIE without control variables and fixed effects. Column (2) adds the fixed effects. Columns (3)-(4) progressively add control variables. In the above four columns, the coefficients of DT all are significant at the level of 1% or 5%. In column (4), every 1% increase in the degree of DT will increase the HEGIE by 0.2%, which reveals that DT can enable HEGIE, and the first hypothesis has been verified. The results also reflect profound economic implications, it suggests that digital technologies have an intrinsic capacity to catalyze greener production methods and innovation strategies among heavy-polluting industries, enabling firms to achieve both economic competitiveness and environmental responsibility.

Table 3. Baseline Regression Results

Variables	(1)	(2)	(3)	(4)
	HEGIE	HEGIE	HEGIE	HEGIE
L.DT	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{**}
	(0.000)	(0.001)	(0.001)	(0.001)
Lev			0.011^{***}	0.013^{***}
			(0.004)	(0.004)
Age			-0.000	-0.000
			(0.000)	(0.000)
TobinQ			-0.001^{**}	-0.001^{**}
			(0.000)	(0.000)
Lnlargest				0.001
				(0.001)
ROA				0.012^{**}
				(0.006)
_Cons	0.501^{***}	0.502^{***}	0.497^{***}	0.493^{***}
	(0.000)	(0.002)	(0.003)	(0.004)
Individual/Year/City fixed effects	No	Yes	Yes	Yes
Obs.	5318	5318	5318	5318
R-squared	0.008	0.128	0.143	0.146

Note: Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Heterogeneity Check Results and Discussion

The benchmark regression findings show that DT has positive effects on improving HEGIE. However, given the complexity of green innovation, the impact of DT on HEGIE may be influenced by enterprise characteristics and regional context.

In general, the availability of resources, market positioning and ability to grow differ significantly when enterprises are in different life cycle stages(Fodor *et al.*, 2024). Therefore, this article intends to investigate whether the effect of DT on HEGIE is influenced by the different life cycle stages of enterprises. Referring to the relevant findings of (Dickinson, 2011), this article divides the sample into growth, maturity and recession periods according to the cash flow of the firms. The results of the subgroups are shown in columns (1)-(3) of Table 4. The coefficients corresponding to growth and maturity periods are significantly positive, while the recession group does not exhibit statistical significance. Such results are reasonable and the possible explanation is that the firms in the growth period usually have higher growth potential and market expansion needs(Habib and Hasan, 2017). DT can help enterprises optimize resource allocation, increase productivity, and reduce resource wastage, thus significantly improving the HEGIE. When an enterprise enters the maturity stage, its organizational system and management norms have been improved, and the profitability tends to be stable, the enterprise will increase investment and accelerate the pace of DT to optimize the existing operational processes and improve production efficiency(Zhao, Yan and Ji, 2023), thus DT at this stage can still play a significant green innovation benefit. Recessionary enterprises commonly suffer from institutional entrenchment, overstaffing and lack of innovation, leading to deteriorating financial conditions that may put high-risk, long-lead-time DT investments on hold(Ryu and Won, 2022). Therefore, the impact of DT on improving the effectiveness of HEGIE may not be significant during recessions. Previous literature has explored the differences in green innovation capabilities as well as environmental governance performance of firms at different life cycle stages(Tariq *et al.*, 2019; Pan *et al.*, 2023), and this article further puts the growth characteristics of firms in the framework of DT and HEGIE, which once again proves the important role of the stage of development of enterprises in green and sustainable development.

Given the differences in resource endowment, policy support and level of economic development among the eastern, central and western regions of China, the geographic location of heavy-polluting enterprises may also be an important factor influencing the greening effect of their DT. In this article, the sample is categorized into three groups and re-tested according to the geographic locations of the enterprises and the basis of classification of provinces by the National Bureau of Statistics (NBS), and the results are reported in columns (4)-(6) of Table 4. The corresponding coefficient for the eastern region is 0.002, significant at the 5% level, indicating that the DT initiatives of enterprises in the eastern region are more effective in promoting green innovation efficiency, which may be related to the better digital infrastructure, talent resources and policy environment in the region. These firms can make full use of digitalization to enhance green innovation efficiency and reduce environmental pollution. Although the positive impact of DT is also statistically significant in the sample of firms in the Central region, the strength of the effect is lower than that in the Eastern region. This may be because the central region faces more challenges in the DT process, such as the limitation of financial and technological resources, as well as the larger proportion of traditional industries, which leads to a higher difficulty in green transformation in the short term. In column (6), the coefficient of Western enterprises is positive but not significant, indicating that the DT of heavy-polluting enterprises in the West has not fully realized the enhancement effect on their HEGIE during the observation period. This may be due to the fact that the industrial structure of the Western region is characterized by a high proportion of traditional industries such as heavy industry, energy and resource extraction. DT in these industries not only requires huge investments, but also involves complex process modifications and the application of environmental governance technologies, making it difficult to achieve significant efficiency improvements in green innovation in the short term. To a certain extent, this also indicates that enterprises in the West still have great challenges in promoting the transformation of green benefits from technology applications. This result is also supported by relevant previous studies(Wang, Ma and Yao, 2024).

Table 4. Heterogeneity Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Growth	Maturity	Recession	East	Central	West
	HEGIE	HEGIE	HEGIE	HEGIE	HEGIE	HEGIE
L.DT	0.002^{**}	0.002^{**}	0.001	0.002^{**}	0.001^{*}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lev	0.017^{**}	0.013^{***}	0.007	0.014^{**}	0.003	0.011^{*}
	(0.007)	(0.004)	(0.006)	(0.006)	(0.002)	(0.007)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Growth	Maturity	Recession	East	Central	West
	HEGIE	HEGIE	HEGIE	HEGIE	HEGIE	HEGIE
Age	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TobinQ	-0.001*	-0.000	-0.001	-0.001*	0.001	-0.001*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Lnlargest	-0.000	0.001	0.002	0.001	0.003	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
ROA	0.022*	0.010*	-0.000	0.014*	-0.006	0.001
	(0.012)	(0.005)	(0.002)	(0.008)	(0.007)	(0.006)
_cons	0.496***	0.495***	0.488***	0.493***	0.482***	0.504***
	(0.006)	(0.005)	(0.011)	(0.005)	(0.010)	(0.012)
Individual/Year/City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2083	2346	889	3250	1031	1037
R-squared	0.198	0.209	0.158	0.124	0.284	0.373

*Note: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.3 Robust Check

Endogeneity Check: First, since omitted variables can trigger endogeneity, given the impact of regional openness on firms' introduction and innovation of technologies, this study adds a control variable at the regional level, i.e., foreign investment (*Foin*), and report the new regression results in column (1) of Table 5. The estimated coefficient of the explanatory variable is 0.002, significant at the 5% level. Second, the article also attempts to incorporate provincial-level fixed effects and shows the results in column (2) of Table 5. The coefficient on DT is significantly positive with a value of 0.002, which validates the robustness of the benchmark regression. Third, to address the concern of sample self-selection, this article uses the PSM method to divide the level of enterprises' DT into two groups according to the mean value, i.e., the one with the higher value of DT is the treatment group. The control variables corresponding to the samples of the two groups are matched 1:1 near-neighbors. The results, as shown in Table 6, demonstrate that the standard deviations of the matched variables after PSM are all within 5% in absolute value, and the t-value is no longer significant, indicating that the PSM is valid. On this basis, column (3) reports the results of the test after PSM, again demonstrating the robustness of the conclusions. Finally, this article selects the average value of DT of firms in the industry as an instrumental variable. A two-stage regression is used and the results are shown in Table 7. Column (1) shows that when the explanatory variable is HEGIE, the estimated coefficient of the regional digital economy remains significantly positive at the 1% level. Moreover, there is no problem with unidentifiable or weak instrumental variables, i.e., the findings remain robust after controlling for possible endogeneity. The value of the F statistic is 40.17, greater than 10, which passes the weak instrumental variable test; the LM statistic is significant at the 1% level, which passes the unidentifiable test. The second-stage regression results show that the regression coefficients of DT and IV are significantly positive, indicating that the core conclusions of this article still hold robustly after mitigating the effects of endogeneity issues.

Other Robustness: This article also uses the following two methods to ensure the robustness of the benchmark regression results at more levels. Firstly, the Tobit method suited for dealing with truncated-tailed variables is considered to replace the original model, and the results are shown in column (4) of Table 5. Secondly, this study excludes samples before 2015 due to the nascent stage of internet development and corporate informatization during China's 12th Five-Year Plan period (2011-2015). It was only post-2015 that these sectors witnessed a more stable and substantial progression. Consequently, this study re-examines and the results are shown in column (5) of Table 5, The effect direction and significance of the DT coefficient are consistent with the basic regression, confirming the robustness of benchmark regression results.

Table 5. Robust Regression Results

Variables	(1)	(2)	(3)	(4)	(5)
	Adding Control variables	Adding Fixed effects	PSM regression	Method	Subsample
	HEGIE	HEGIE	HEGIE	HEGIE	HEGIE
L.DT	0.002**	0.002**	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Foin	-0.000		0.016***	0.013***	0.015***
	(0.000)		(0.003)	(0.001)	(0.005)
Lev	0.013***	0.013***	-0.000	-0.000	0.000
	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)
Age	-0.000	-0.000	-0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TobinQ	-0.001**	-0.001**	0.003***	0.001**	0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Lnlargest	0.001	0.001	0.006	0.012***	0.012*
	(0.001)	(0.001)	(0.007)	(0.004)	(0.006)
ROA	0.012**	0.012**	0.483***	0.493***	0.491***
	(0.006)	(0.006)	(0.012)	(0.006)	(0.005)
_cons	0.493***	0.493***	0.002***	0.002***	0.002***
	(0.004)	(0.004)	(0.001)	(0.000)	(0.001)
Individual/Year/City fixed effects	Yes	Yes	Yes	Yes	Yes
Province *fixed effects*	No	Yes	No	No	No
Obs.	5318	5318	2250	5318	3977
R-squared	0.146	0.146	0.166	--	0.177

Note: Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. PSM Balance Test Results

Variables	Sample	Mean		%Bias	t-test	
		Control	Treatment		t	P>|t|
Lev	Unmatched	0.429	0.452	11.4	3.85	0.000
	Matched	0.429	0.452	2.4	0.67	0.502
Age	Unmatched	20.123	21.824	30.6	10.70	0.000
	Matched	21.926	21.824	-1.8	-0.51	0.611
TobinQ	Unmatched	2.020	1.868	-12.1	-4.03	0.000
	Matched	1.902	1.868	--2.7	-0.81	0.420
Lnlargest	Unmatched	3.465	3.460	-1.2	-0.41	0.683

	Matched	3.436	3.460	5.1	1.44	0.150
ROA	Unmatched	0.037	0.039	3.2	1.13	0.260
	Matched	0.038	0.039	0.9	0.27	0.787

Table 7. Endogeneity Issues-Instrumental Variable

Variables	(1)	(2)
	First-stage regression	Second-stage regression
	DT	HEGIE
IV tool	0.800***	
	(0.126)	
L.DT		0.007**
		(0.003)
Lev	0.261**	0.011***
	(0.120)	(0.004)
Age	0.009	-0.000
	(0.056)	(0.000)
TobinQ	-0.048***	-0.000
	(0.050)	(0.000)
Lnlargest	0.072	0.001
	(0.050)	(0.001)
ROA	0.452	0.009
	(0.235)	(0.006)
_Cons	-0.638***	0.496***
	(0.218)	(0.004)
LM statistic	33.31***	
F statistic	40.17***	
Individual/Year/City fixed effects	YES	YES
Obs.	5318	5318

Note: Standard errors in parentheses
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

4.4 Further Examination and Discussion

Knowledge Resources: To further reveal the mechanism by which DT affects HEGIE, two mediating variables related to knowledge resources were included in the empirical model(Orsatti, 2023), i.e. the Patent citation (PC) and knowledge width (KW). The former is usually considered an important indicator of the influence of technology in the existing literature generally to characterize knowledge flow(Akcigit, Baslandze and Stantcheva, 2016). The knowledge width represents the degree of diversity of knowledge and its measurement method is shown in Equation (8).

$$KW_{i,t} = 1 - \sum \alpha^2 \qquad (8)$$

Where, α represents the proportion of each category in the patent classification number. The larger the value of $KW_{i,t}$, the greater the difference between the patent classification numbers at each group level, indicating the higher knowledge width. These data were obtained from the China Innovation Patent Research Database and the website of the China National Intellectual Property Administration. The results of the mechanism check are shown in Table 8. Columns (1)-(2)

correspond to the transmission effect of patent citation, and columns (3)-(4) correspond to the knowledge width. In columns (1)-(4), the estimated coefficients corresponding to the core mechanism variables PC and KW are both positively significant, indicating that DT can motivate the allocation of knowledge resources, which in turn promotes the HEGIE. The second hypothesis has been empirically proven. This highlights the huge role of DT in catalyzing green innovation capabilities. The ability of DT initiatives to benefit the allocation, optimization and recycling of knowledge resources in traditional micro-enterprises, and to improve the efficiency of knowledge dissemination, integration and utilization, thereby contributing to the enhancement of HEGIE, can also be considered the huge potential of DT in driving innovation and economic progress.

Table 8. Knowledge Resources

Variables	(1)	(2)	(3)	(4)
	PC	HEGIE	KW	HEGIE
L.DT	0.130^{***}	0.002^{**}	0.016^{**}	0.002^{**}
	(0.049)	(0.001)	(0.008)	(0.001)
PC		0.001^{**}		
		(0.001)		
KW				0.002^{**}
				(0.001)
Lev	0.849^{***}	0.012^{***}	0.050	0.012^{***}
	(0.236)	(0.004)	(0.041)	(0.004)
Age	0.008	-0.000	0.003	-0.000
	(0.012)	(0.000)	(0.002)	(0.000)
TobinQ	-0.113^{***}	-0.001^{*}	0.004	-0.001^{**}
	(0.029)	(0.000)	(0.005)	(0.000)
Largest	0.001	0.001	0.010	0.001
	(0.106)	(0.001)	(0.018)	(0.001)
ROA	2.797^{***}	0.008^{*}	0.252^{***}	0.011^{**}
	(0.424)	(0.004)	(0.082)	(0.005)
_Cons	0.828	0.492^{***}	0.122	0.492^{***}
	(0.528)	(0.004)	(0.077)	(0.004)
Individual/Year/City fixed effects	Yes	Yes	Yes	Yes
Obs.	5318	5318	5318	5318
Pseudo R-squared	0.443	0.153	0.287	0.147

Note: Standard errors in parentheses
* *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

Slack Resources: To verify the role of different redundant resources in the impact of DT on HEGIE, we tested the mechanism based on the flexibility of resources. Referring to the existing literature(Wiseman and Bromiley, 1996; Chiu and Liaw, 2009), this article uses the current ratio (High_slack) as a representation of high discretion slack resources, and the ratio of management expense to operating income (Low_slack) as a proxy variable for low discretion slack resources. Table 9 reports the results. Columns (1)-(2) correspond to the transmission effect of low discretion slack, the coefficients of Low_slack and DT are significantly negative in column (2), yet the coefficient of DT is significantly positive, indicating that DT induces the low discretion slack resources and further exerts a positive impact on HEGIE, which supports the hypothesis H3a. Columns (3)-(4) display the effect of high discretion slack resources as an essential mechanism. The results demonstrate the rationality of hypothesis H3b, as the regression coefficient of High_slack is positive significantly. This indicates that high discretion slack resources can be seen as an important channel for DT to stimulate HEGIE improvement. In conclusion, the results show that for HEGIE, DT can create broader innovation opportunities for enterprises by unlocking the potential of both high and low discretionary idle resources. DT can enable firms to automate and intelligently schedule production, more accurately predict market demand with the help of big data and AI technologies, and avoid overcapacity and inventory buildups, which would vigorously reduce firms' rigidity in production, and overall Improve HEGIE.

Table 9. Slack Resource

Variables	(1)	(2)	(3)	(4)
	Low Discretion Slack		High Discretion Slack	
	Low_slack	HEGIE	*High_slack*	HEGIE
L.DT	-0.009***	0.002**	0.060***	0.002**
	(0.002)	(0.001)	(0.019)	(0.001)
High_slack				0.001**
				(0.000)
Low_slack		-0.012***		
		(0.004)		
Lev	-0.023	0.012***	-3.070***	0.015***
	(0.014)	(0.004)	(0.104)	(0.005)
Age	-0.001	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.004)	(0.000)
TobinQ	0.006***	-0.001**	0.038***	-0.001**
	(0.002)	(0.000)	(0.013)	(0.000)
Lnlargest	-0.014**	0.001	0.086*	0.001
	(0.006)	(0.001)	(0.044)	(0.001)
ROA	-0.108***	0.010**	0.087	0.011**
	(0.029)	(0.005)	(0.203)	(0.005)
_cons	0.131***	0.494***	2.722***	0.490***
	(0.032)	(0.004)	(0.183)	(0.005)
Individual/Year/City fixed effects	Yes	Yes	Yes	Yes
Obs.	5318	5318	5318	5318
R-squared	0.206	0.150	0.647	0.147

Note: Standard errors in parentheses
* *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

5. Conclusions and insights

5.1 Conclusions

The results of the study show that DT of enterprises in heavy-polluting industries has a beneficial impact on HEGIE, which implies that DT is an effective strategy for heavy-polluting enterprises pursuing green transformation and upgrading. However, the above relationship is influenced by the development stage and geographical location of enterprises. Enterprises in the growth and maturity stages and Enterprises located in the East and Central regions are more likely to benefit from DT in terms of green innovation efficiency. In addition, based on the open innovation theory and the resource-based view, this study identifies two transmission mechanisms, which are the optimization of knowledge resources and the allocation of idle resources. DT facilitates HEGIE by enhancing knowledge flows, knowledge width, and efficiency in the use of high-discretion slack resources and by reducing low-discretion slack resources. Further, the findings of this study may also be largely applicable to other developing countries, with far-reaching implications for developing countries aiming to balance economic growth with environmental sustainability. Heavy industry often plays a crucial role in economic growth, and DT offers these countries a viable path towards a green transition. Given the resource constraints and transformation challenges faced by many developing countries, this finding is particularly important to inspire countries to share best practices and experiences on DT and promote a more sustainable global industrial pattern.

5.2 Theory Contribution

First, this research greatly broadens our understanding of the microeconomic benefits of digital transformation and breaks the narrow focus of green innovation on green patent outputs. As global competition intensifies, heavy-polluting industries, as distinctive and traditional sectors of the economy, should no longer be solely output-centered, but improving green innovation efficiency should become a more ambitious goal. By elucidating the patterns and mechanisms through which digital transformation affects green innovation efficiency, this study contributes to a deeper understanding of how contemporary industries rely on technological advances to achieve sustainable growth, which highlights the harmonious convergence of technical rationality and value rationality. Second, this study expands the research scope and depth of the open innovation theory and resource-based view, reveals the law of digital transformation on green innovation efficiency by integrating the open innovation theory and resource-based view, and emphasizes the importance of digital transformation to enhance the intellectual capital accumulation and resource allocation capacity of enterprises, which not only enriches the existing theoretical perspectives, but also explores the digital transformation of heavy-polluting enterprises in the future, research on the relationship between internal knowledge resources and redundant resource management and green sustainability capability provides new insights.

5.3 Practice implications

Firstly, The Government should encourage heavy-polluting industries to actively adopt DT strategies to improve the efficiency of green innovation. This includes developing a comprehensive digital transformation roadmap and adopting cutting-edge technologies such as artificial intelligence, the Internet of Things and big data analytics. To accelerate this process, policymakers should provide fiscal incentives, such as tax breaks and grants, specifically designed to support DT programs that directly contribute to environmental sustainability.

Second, our research underscores the criticality of contextual factors in mediating the DT-HEGIE relationship. Enterprises in nascent phases or peripheral regions may require bespoke interventions to fully capitalize on DT's potential for green innovation. Consequently, policymakers and business leaders should consider the unique dynamics of each enterprise's growth trajectory and geographical setting when formulating strategies for digital transformation. By doing so, they can foster a more inclusive and environmentally conscious digital landscape, where technological progress and ecological preservation are not mutually exclusive but complementary forces driving sustainable development.

Thirdly, the mediating role of knowledge capture and slack resources offers inspiration. To fully realize the potential of DT in enhancing the efficiency of green innovation, governments should foster a business environment for enterprises that is conducive to the interoperability of knowledge resources, for example, by promoting open innovation ecosystems and encouraging knowledge-sharing among enterprises, academic institutions and technology companies. It is also important to develop guidelines and frameworks for the management of high-discretionary idle resources to ensure optimal utilization in green innovation activities. Low-discretionary idle resources should be minimized through lean management facilitated by digital tools to reduce innovation costs. In this way, companies will be able to better utilize their resources to drive green innovation and make significant progress towards environmental sustainability

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Appendix A: Classification of heavy-polluting industries

Industry Code	Industry Name
B06	Coal mining and washing industry
B07	Oil and gas extraction industry
B08	Mining and dressing industry of ferrous metal ore industry
B09	Non-ferrous metal mining and dressing industry
C17	Textile industry
C19	Leather, fur, feathers, and its products industry
C22	Paper and paper products industry
C25	Petroleum processing, coking, and nuclear fuel processing industry
C26	Chemical raw materials and chemical products manufacturing industry
C27	Pharmaceutical manufacturing industry
C28	The chemical fiber manufacturing industry
C30	Plastic product industry
C31	Non-metallic mineral products industry
C32	Ferrous metal smelt and calender processing industry
C33	Non-ferrous metal and calender processing industry
D44	Power and heat production and supply industry

Appendix B: Enterprise carbon emissions calculation

This study adopts the factor conversion method based on operating costs. First, the ratio between the operating cost of the enterprise and the corresponding industry operating cost is calculated, and then the ratio is multiplied by the industry CO2 emissions as follows.

$$EC_{k,t} = \frac{OC_{k,t}}{OC_{i,t}} * EC_{i,t}$$

Where, $EC_{k,t}$ represents the carbon dioxide emissions of heavy-polluting enterprises, $EC_{i,t}$ represents the carbon dioxide emissions of certain industries. $OC_{i,t}$ is the operating costs of the industries. $OC_{k,t}$ represents the operating costs of the enterprises.

Appendix C: DT Thesaurus

Dimension	Related Words
Artificial Intelligence Technology	Artificial intelligence, business intelligence, image understanding, investment decision support system, intelligent data analysis, intelligent robots, machine learning, deep learning, semantic search, biometric identification technology, face recognition, voice recognition, identity verification, autonomous driving, and natural language processing.
Cloud Computing Technology	Cloud computing, stream computing, graph computing, internal memory computing, multiparty secure computing, brain-inspired computing, green computing, cognitive computing, fusion architecture, billion-level concurrency, exabyte-level storage, internet of things, Cyber-physical system
Big data technology	Big data, data mining, text mining, data visualization, heterogeneous data, credit, augmented reality, mixed reality, virtual reality
Blockchain technology	Blockchain, digital currency, distributed computing, differential privacy technology, intelligence financial contracts
Digital technology application	Mobile Internet, industrial Internet, mobile Internet, internet medical, E-commerce, mobile payment, third-Party payment, NFC payment, smart energy, B2B, B2C, C2B, C2C, O2O, network connection, smart wear, smart agriculture, smart transportation, smart healthcare, smart customer service, smart home, smart investment advisory, smart cultural tourism, smart environmental protection, smart grid, smart marketing, smart marketing, unmanned retail, internet finance, digital finance, Fin-tech, financial technology, quantitative finance, open banking