ISSN: 1813-4890

Impact of Digital Transformation on Technological Progress in Heavily Polluting Industries

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Abstract

The digital age has brought new opportunities to many companies, and they are undergoing a profound transformation to take advantage of those opportunities. Identifying ways to combine digital technology with traditional methods of production and development. This has become a research focus for research in various industries. The pollution levels in China between 2001 and 2020 are based on heavy-polluting enterprises. The results of this study confirm that digital transformation contributes positively to technological progress in heavy-polluting industries. In this study, we find that digital transformation significantly contributes to technological advancements and that the relationship is stronger in R&D-intensive firms, state-owned enterprises and SMEs. Using a mechanism analysis, we found that with the advent of digital technology, enterprises have increased their investment in research funding. This has led to accelerated technological progress and optimization of human resource deployment, reduced enterprise management costs, and ultimately, accelerated technological advancement. Providing insights into how heavy pollution enterprises can promote digital transformation and revolutionize their business models through digital transformation, it reveals the intrinsic impact of digital transformation on heavy pollution enterprises.

Keywords

Digital Transformation; Heavily Polluting Industries; Technological Advances; Business Models.

1. Introduction

As emerging technologies dominate the digital world, global development is gradually shifting from an industrialized model to a digital one. Despite China's rapid economic growth, digital transformation has posed a challenge to a certain extent, it has also had a far-reaching impact on China’s enterprises’ technological progress. All industries are now affected to varying degrees by the impact of digitization, which is often accompanied by fundamental changes in business operations and management. Organizations are undergoing fundamental changes in their business models at an industry level that have a significant effect on business practices at a fundamental level as a result of digital transformation. For example, the development of increasingly advanced digital technologies has prompted most business leaders to reorganize enterprise structures. In addition, enterprises use state-of-the-art digital technologies to transform the pathways to value creation; this is crucial in allowing enterprises to remain competitive . In response to changing market demands, digital transformation requires frequent adjustments to processes, services, and company culture and products[1].Digital technology plays a central role in facilitating social change, economic benefit, corporate technological innovation, and industry-wide green and efficient development[2]. Digital transformation advantageous sustainable development.

ISSN: 1813-4890

Emerging digital technologies have penetrated and revitalized various industries, including heavily polluting industries[3]. In the petrochemical industry, optimization of production control using digitisation technology has helped traditional manufacturing process to dynamically adapt to severe market environments, thereby improving corporate efficiency[4]; In the mining industry, supervised machine learning techniques enables real-time monitoring of mine compressive strength, tensile strength, and prediction of roadheader performance indices [5]; moreover, the powerful visual processing capabilities of deep learning, with the help of efficient algorithms (e.g., neural network algorithms), can identify the locations of mineral resources, classify different categories of mineral resources, and screen resources of varying purity, which significantly improves the efficiency of mining. The digitalization of the energy sector is increasing, with more companies taking advantage of it, to improve the reliability and durability of their products and developing cutting-edge green innovative technologies and production processes that increase energy efficiency. Energy companies that embrace digital technologies into their business model, see improved efficiency, lower costs, revitalized energy plants, well-established industry, supply and distribution chains, and a wealth of other benefits [6].

Heavy polluting industries face particular challenges in relation to sustainable development and the goal of "double carbon," including optimization and upgrading of industrial structures, green environmental protection, carbon reduction, and low industrial competitiveness on a rapid scale [7]. Since the 20th National Congress in China, the term 'digital transformation and development' has been frequently mentioned in government reports, and a series of major policy decisions have been proposed as a result. In 2020, China set a "dual-carbon" target, which includes the introduction of cutting-edge and digital technology talent to the world around us and heavy polluting industries. Technological advances include industrial structure optimization, high-tech innovation, green transformation, efficiency improvements in energy use, and significant reductions in environmental pollution. However, most heavily polluting industries in China still do not fully recognize the power of digital transformation for technological progress.

An overview of digital transformations in heavy polluting industries in China is presented in this study to address this issue. In particular, it was the purpose of this study to determine: (1) How digital transformation can promote technological progress in industries with heavy pollution; (2) aspects of digital transformation are affected by technological progress in heavily polluting industries; and (3) digital transformation effects are heterogeneous based on enterprises' nature and size. Chinese A-share companies with heavy pollution were selected. Based on this sample, we constructed a panel data model to study how digital transformation impacts their technological progress. The mechanisms of impact were analyzed from three perspectives, the heterogeneity of the impacts was assessed in reference to ownership structure, the size of the enterprise, and research and development (R&D) investments. To compensate for deficiencies in existing studies, the following contributions have been made as a result of this study: (1) targeted research sample selection designed to reduce pollution from heavily polluting enterprises and avoid the research bias that arises by selecting enterprises from across different industries; (2) From the perspective of enterprise R&D investment and output, this paper explores the mechanism between digital transformation and the progress of heavily polluting technologies; and(3) analyzed the heterogeneous impact of digital transformation on the technological progress of heavily polluting firms based on the dimensions of an enterprise, firm size and R&D investment scale.

2. Literature Review and Theoretical Hypotheses

2.1. Research on digital transformation

A key component of China's socialist market economy, the digital economy supports major national economic strategies. Innovation-driven development has been greatly facilitated by the digital economy's development. The digital economy promotes supply-side structural reform, facilitates the development of innovative technologies and enhances enterprises' ability to realise quick cash. To accomplish this, researchers have begun exploring enterprise digital transformation's connotations.

Karagiannaki[8] argued that enterprise firms use digital transformation to improve their performance or market influence through the use of high technology. Enterprise digital transformation involves organizations using emerging digital technologies to improve their business. This includes enhancing customer loyalty, optimizing business operations strategies, and transforming business models[9]. An enterprise's digital transformation is the process of digitizing its production, sales, business models, and marketing strategies, and services that are used to either replace traditional physical products or to make them more competitive [10]. A subset of scholars argue the digital transformation of enterprises as revolutionizing their traditional business activities, accelerating their production processes, business models, and high-tech transformation of the industrial chain, positioning themselves in an advantageous market position by taking full advantage of the opportunities offered by digital technologies with highest priority and strategic position [11]. Considered the traditional technologies and the powerful impact of emerging digital, enterprises are becoming more digitally transformed by either radically transforming their business models or introducing new ones [12].

From a macro perspective, economic development's impact on digital transformation is largely examined in existing literature. In addition to expanding the enterprise technology market, digital transformation has been shown to lead to greater market penetration[13]. As an example of how emerging digital technologies can be applied to industrial firms. Luo[14] found that e-commerce finance contributes significantly to enterprises' digital transformation. Li[15] and Niu[16] showed that enterprises' innovative development is positively correlated digital transformation has forced enterprises to carry out innovative technological research and development, alleviate financial constraints, improve corporate governance, and take a series of other measures to promote core technological change. Digital transformation improves business performance by reducing costs, increasing revenues, and boosting efficiency[17]. Enterprises can benefit from digital transformation by strengthening supply-side structural reforms, enabling high-quality development, and providing a strong stimulus to innovation and development. In recent years, more scholars have conducted microenterprise-related research due to new developments in digital technology and the online economy. By transforming traditional manufacturing industries, digital transformation can improve business relationships, reduce cybersecurity risks, increase employment of low-skilled workers, and protect intellectual property [18].

As traditional manufacturing industries transform into digital enterprises, the power gap in relationships will be balanced, cybersecurity issues will be addressed, low-skilled workers will be employed, and intellectual property rights will be protected.

By implementing advanced innovative technologies and processes, large-scale enterprises attempt to improve energy efficiency, increasing reliability and durability (materials and mechanical engineering), thereby reducing operating costs and maximizing efficiency[6]. Considering that computers cannot completely replace human labour today, digital transformation affects the employment situation in today's world, and digital transformation allows companies to use emerging digital technologies to perform complex tasks without human intervention, allowing them to produce and realize their products more efficiently[19].

In addition, digital transformation can lead to greater resilience to market changes and financial risks by increasing operational flexibility and expanding financing options [20].

2.2. Technological advances in heavy pollution industries

Technological progress can be categorized into two main areas: technological innovation and technological introduction[21]. Strengthening the technological innovation capacity of enterprises helps them master cutting-edge digital technologies, by doing so, they will gain more market share and enhance their risk management capabilities[22]. SMEs can close the technology gap with oligopolies and accelerate their technological progress in a short period of time by introducing emerging digital technologies[23]. For heavy pollution industries, especially those centered on fossil fuel consumption, such industries are faced with aging industrial structures, a lack of core technological innovation, energy inefficiency, pollution, and other dilemmas. Technological progress offers a route for heavily polluting enterprises to address these issues and recapture market relevance.

Most existing literature on technological advances in heavily polluting industries is unable to avoid green technological innovation. With the advent of Industrial Age 4.0, the state has attached increasing importance to environmental protection. Enterprises are subject to carbon emission targets, energy consumption targets and environmental regulations, which have led to profound technological innovation, product replacement, institutional optimization and eco-innovation[24]. For heavy polluters, technological progress can bring about an increase in productivity per unit of labor, contributing to an increase in total factor productivity at the industry level. Environmental regulators have issued a series of green and sustainable development strategies to force heavy polluters to make technological progress[25]. Enterprises technological progress affects their industrial structure and factor income share[26].

2.3. Research on digital transformation and Polluting industries make technological advances

Literature that directly links technological progress in heavily polluting industries to digital transformation is scarce. However, most studies examine enterprises' technological progress due to digital finance. A further benefit of digital finance is that it facilitates technological advancements by increasing transparency for consumers about business operations and production methods, which results in more effective financial flows. [27]. Digital finance has led to technological advances by encouraging companies to optimize and restructure their industrial structures, as well as improve the competitiveness of their products[28]. In addition to reducing financing constraints among enterprises, Lin and Ma[29] suggest increasing R&D investments and alleviating financial constraints to achieve technological progress, as well as forcing enterprises to invest in R&D and alleviate financial constraints. The arrival of digital transformation has prompted the rapid development of digital finance, which can effectively alleviate the financing of heavily polluting enterprises to optimize their operational model and thus promote their technological progress, while some of the digital finance policies introduced by the government can specifically bring lucrative economic benefits to enterprises[30], and at the same time help heavily polluting enterprises to achieve comprehensive and gradual technological progress. However, green credit policies also hinder heavy polluters from making radical technological progress to a certain extent[31]. Another positive aspect of the green finance movement is its positive impact on technological progress in polluting firms, particularly state-owned enterprises, and firms with higher non-compliance costs[32]. Green bonds help enterprises obtain sufficient working capital, reduce the pressure of capital turnover, and enhance their ability to realize quick financing, which promotes technological progress[33].

Additionally, existing research indicates a number of areas that deserve further investigation. In the first place, though some scholars have studied how digital transformations affect companies' technological progress, most chose industry-wide enterprises as research samples. Due to a lack of empirical evidence, however, it is important to note that industries-specific research is critical to digital transformation of heavy pollution enterprises. Second, in most existing research, the mechanisms of digital transformation affect technological progress from the perspective of technology capability enhancement, while HR and R&D investment are neglected. Finally, existing studies have not considered the heterogeneous effects of digital transformation with respect to ownership structure, enterprise size and technological advancement of firms.

2.4. Theoretical hypotheses

2.4.1. Hypothesis 1

Technology progress and digital transformation are complex topics that can be analyzed from many theoretical perspectives[34]. The following are a few common theoretical analyses: the diffusion of innovation theory suggests that digital transformation provides innovation-enabling technology platforms and tools that facilitate innovation diffusion and adoption; transformation allows companies to introduce new technologies faster and achieve scale adoption. Innovation diffusion can drive technological progress and promote economic growth. Disruptive innovation theory suggests that advancing technologies and business models brought about by digital transformation may threaten traditional industries and markets. Through digital transformation, organizations can achieve more efficient, flexible, and innovative business models that replace old ways of doing things in traditional industries. Disruptive changes brought about by such innovations may accelerate technological progress and market competition. Intellectual capital theory emphasizes digital transformation's importance for knowledge. Digital transformation facilitates information and knowledge exchange. This facilitates intellectual capital creation. Intellectual capital is a driving force for technological progress and innovation, which can be accelerated through learning and knowledge sharing through digital transformation. Digital transformation positively impacts economic growth by increasing productivity and efficiency and fostering innovation and competition. Through digital transformation, companies can optimize business processes, reduce costs, expand markets, and accelerate technological progress, thereby achieving long-term economic growth.

Hypothesis 1 (H1) was as follows: Digital transformation can significantly contribute to technological progress in heavily polluting industries.

2.4.2. Hypothesis 2

HRM has been impacted greatly by digital transformation. Digital transformation drives the use of automation and intelligent technologies. These technologies can replace traditional repetitive, low-value-added tasks and enable HR departments to better focus on strategic and high-value tasks. Digital transformation allows for more personalized and customized employee management and development. Through digital platforms and online training tools, HR departments can offer more flexible, timely and personalized training and development programs that improve employees' skills and qualities. This will increase their loyalty and engagement with the organization.

Optimizing the HR department can lead to technological advancement. HHR drives advancement by recruiting and attracting high-caliber employees, especially those with technical expertise and innovation. Human resources department participates in the enterprise's technology assessment and planning process, understands the enterprise's technology needs and development direction, predicts talentwise talent through sensitivity to the technology trend and market change, and provides strong human resources support for the enterprise's technological progress.

Hypothesis 2 (H2) was as follows: Digital transformation leads to optimal deployment of HR within an enterprise, accelerating technological progress.

2.4.3. Hypothesis 3

In terms of R&D investments, digital transformation has a significant impact. Digital transformation drives innovation in technologies and innovations. Organisations need to invest more resources in developing, testing and applying these cutting-edge technologies to compete in the market and meet consumer needs. Enterprises require buildings to provide effective R&D facilities. They must work closely with business units to understand market demand and future trends. They need to synchronise strategic planning and technology development, R&D investment and strategic orientation. Enterprises increase their investments in technology industrialisation and transform R&D results into actual products and services through market promotion and commercial application. This can accelerate technology transition and promotion and promote technological progress through daily communication. R&D investments can help companies maintain a competitive edge in technology. Through continuous product and service innovation and product upgrading, enterprises can provide more competitive products and services to meet consumer demand. This can help enterprises win more market share and promote industrial development and technological progress.

Hypothesis 3 (H3) was as follows: Digital transformation leads to increased investment in research within companies, thereby accelerating technological progress.

3. Research Design

3.1. Variable selection

(1) Explained variables: technological progress was measured based on (1) total factor productivity (TFP) on a corporate level (Zhou and Du,2021), the LP method (Productivity function estimation using intermediate inputs to represent unobservable productivity terms) .Levinsohn and Petrin[35] is used to measure it, and finally we get the complete enterprise-level total factor productivity data. For the subsequent robustness test, a second explanatory variable selected was the number of invention patent applications filed by heavy polluting enterprises ($IApply$). The natural logarithm of the number of invention patent applications for a given company was used to calculate ($IApply$).

(2) Hence, the index of the degree of digital transformation of enterprises was the core explanatory variable in this study ($Tdodt$). Among the methods used to obtain $Tdodt$, text analysis of annual reports of listed companies was the primary method; however, some data were also extracted from the CSMAR database. In order to minimize the effect of heteroskedasticity and mitigate the effect of possible outliers, some of the data were logarithmized. The levels of continuous variables were 1% and 99%.

(3) Control variables: among the control variables in this study were total assets(TA) , operating income (OI)[36], depreciation and amortization (DA)[37], asset structure (AS), book-to-market ratio (BC) [38], investment expense ratio (IER), Tobin's Q ($Tobin\ Q$)[39], and enterprise size($SIZE$)[40].

A description of the main variables is provided in Table 1. A description of the main variables is provided in Table 2.

Table 1 An explanation of the main variables

Variable type	Variable name	Variable abbreviation	Definition
Explained	Total factor	TFP	Ratio of total output to total factor inputs

ISSN: 1813-4890

variable	productivity		
	Number of patent applications for inventions	IApply	Annual number of invention patent applications filed by the enterprise
Explanatory variable	The degree of digital transformation	Tdodt	Frequency statistics: ratio of exact words to total words
Control variable	Total assets	TA	Sum of total business assets
	Revenue	OI	Sum of total business revenues of the enterprise
	Depreciation and amortization	DA	Depreciation of assets, amortization of expenses
	Asset structure	AS	Net fixed assets to net inventories ratio
	Book-to-market ratio	BC	Market capitalization to shareholders' equity ratio
	Investment expenditure rate	IER	Amount paid for property, plant, equipment, and other long-term assets compared to total assets
	Tobin Q	Tobin Q	Replacement cost of capital to its market value
	Company size	Size	Total assets divided by the natural logarithm

Table 2 Statistic description of main variables

Variable	Obs	Mean	SD	Min	P25	P75	Max
TFP	1335	7.133	0.872	3.780	6.490	7.791	10.108
Tdodt	1335	0.438	0.358	0.019	0.222	0.551	5.041
TA	1335	22.972	1.514	19.886	21.836	24.000	28.636
OI	1335	22.596	1.622	17.273	21.405	23.745	28.718
DA	1335	19.455	1.730	12.420	18.141	20.704	26.112
AS	1335	0.484	0.165	0.004	0.368	0.602	0.908
BC	1317	0.733	0.246	0.137	0.550	0.931	1.323
IER	1335	0.063	0.051	0.000	0.026	0.084	0.449
TobinQ	1317	1.595	0.782	0.756	1.075	1.819	7.322
Size	1335	22.596	1.622	17.273	21.406	23.744	28.718
IApply	1335	2.454	1.398	0.693	1.386	3.296	8.498

3.2. Benchmark regression modeling

This study constructed the following model to determine how enterprise digital transformation impacts heavy pollution industry technological progress:

$$TP_{i.t} = \beta_0 + \beta \mathrm{Tdodt}_{i.t} + \sum \mathrm{Controls}_{i.t} + \mathrm{Year} + \mathrm{Id} + \varepsilon_{i.t} \quad (1)$$

Individuals in the sample and years between the samples are denoted by subscripts i and t; a random disturbance term is ε; β and β_0 are parameters to be estimated; TP denotes the technological progress of heavy polluting firms; $Tdodt$ represents the degree to which firms are digitally transformed; the control variable is $Controls$; and $Year$ and Id denote the year and the enterprise's individual fixed effects, respectively.

3.3. Threshold modeling

(1) The R&D investment threshold model was as follows:

$$TP_{it} = \mu_i + \alpha_1 Controls_{it} + \beta_1 Tdodt_{it} * Q(q_{it} < \gamma) + \beta_2 Tdodt_{it} * Q(q_{it} \geq \gamma) + e_{it} \quad (2)$$

The subscripts$i$ and t indicate the i^{th} listed company and the t^{th} year, respectively; γ is the threshold value; The indicative function (dummy variable) is $Q(\cdot)$; the control variable is $Controls$; e_{it} is the stochastic perturbation term; q_{it} is the threshold variable; The threshold variable for this part is "R&D investment as a percentage of operating income".

(2) The Threshold model for optimal deployment of HR was as follows:

$$TP_{it} = \mu_i + \alpha_1 Controls_{it} + \beta_1 Tdodt_{it} * Q(q_{it} < \eta_1) + \beta_2 Tdodt_{it} * Q(\eta_1 \leq q_{it} < \eta_2) + \beta_3 Tdodt_{it} * Q(q_{it} \geq \eta_2) + e_{it} \quad (3)$$

where η_1 and η_2 are the thresholds of two different levels, "cash paid to and for employees" was selected as the threshold variable other variables are the same as those in equation (2).

3.4. Data sources

In the initial sample, all Chinese A-share listed companies from 2001 to 2020 were screened based on the following criteria. (1) Companies that operate in heavy polluting industries were identified in accordance with the notice of "Classification and Management Catalog of Listed Companies in Environmental Verification Industry" issued in 2008. (2) Companies with ST, *ST, and financial anomalies with gearing ratios > 100% were excluded. (3) Heavily polluting listed companies with missing key variables were excluded. After screening, 1335 sample data were obtained.

4. Empirical Findings

4.1. Base regression analysis

Based on a benchmarking regression model, Table (3) reports the results of the benchmarking back of the impact of digital transformation on heavy polluters' technological progress. Columns (1), (2), (3), (4), and (5) in Table (3) show the results of mixed effects (MEM), individual one-factor fixed effects (Id-FEM), individual one-factor random effects (Id-REM), time one-factor fixed effects (T-FEM), and time one-factor random effects (T-REM) regressions respectively, with regression coefficients of 0.0567, 0.0881, 0.0883, -0.0412, 0.0567, where the regression results of mixed effects (MEM) and time single-factor random effects (T-REM) were significantly positive at the 5% level; the regression results of individual single-factor fixed effects (Id-FEM) and individual single-factor random effects (Id-REM) were significantly positive at the 1% level; The regression results for the one-factor fixed effects of time (T-FEM) were not significant. Meanwhile, joint "individual and time" fixed effects are also used to account for changing firm-level unobservable. As shown in Column (6), the two-factor control effects (Id-T-DFEM) regression of firms' individual fixed effects (Id-FEM) regression with a regression coefficient of digital transformation of 0.0459 is significant at the 5% level. The above results can fully demonstrate that digital transformation can significantly promote technological progress in heavy pollution industries, supporting the previous hypothesis (H1).

Table 3. Test results for benchmark regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	TFP	TFP	TFP	TFP	TFP
	MEM	Id-FEM	Id-REM	T-FEM	T-REM	Id-T-DFEM
Tdodt	0.0567**	0.0881***	0.0883***	-0.0142	0.0567**	0.0459**
	(2.18)	(3.90)	(4.39)	(-0.53)	(2.18)	(2.01)
TA	-0.156***	-0.412***	-0.351***	-0.160***	-0.156***	-0.430***

	(-6.29)	(-16.82)	(-16.43)	(-6.47)	(-6.29)	(-16.76)
OI	0.813***	0.981***	0.908***	0.816***	0.813***	0.939***
	(49.58)	(48.38)	(53.86)	(50.34)	(49.58)	(45.32)
DA	-0.195***	-0.0530***	-0.0759***	-0.201***	-0.195***	-0.0550***
	(-11.16)	(-3.85)	(-5.76)	(-11.83)	(-11.16)	(-4.21)
AS	-0.266***	-0.694***	-0.714***	-0.114*	-0.266***	-0.623***
	(-3.83)	(-10.42)	(-11.91)	(-1.67)	(-3.83)	(-9.71)
BC	-0.299***	0.0336	-0.00994	-0.359***	-0.299***	-0.102
	(-3.54)	(0.55)	(-0.17)	(-4.20)	(-3.54)	(-1.58)
IER	-0.970***	-0.559***	-0.687***	-0.505***	-0.970***	-0.329**
	(-5.32)	(-4.23)	(-5.57)	(-2.65)	(-5.32)	(-2.42)
TobinQ	-0.0670***	0.00229	-0.000751	-0.0707***	-0.0670***	-0.0128
	(-2.76)	(0.14)	(-0.05)	(-2.96)	(-2.76)	(-0.79)
_cons	-3.364***	-4.228***	-3.490***	-3.247***	-3.364***	-2.726***
	(-17.73)	(-14.78)	(-16.88)	(-17.17)	(-17.73)	(-7.74)
Year FE	NO	NO	NO	YES	NO	YES
Firm FE	NO	YES	NO	NO	NO	YES
N	1317	1317	1317	1317	1317	1179
F	1005.3	569.8		1023.4		349.6
r2	0.860	0.834		0.864		0.979

t statistics in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.2. Heterogeneity analysis

4.2.1. A heterogeneous nature of business ownership

In the context of rapid economic development, enterprises need to maximize their market competitiveness. To this end, China's state-owned enterprises (SOEs) are in a better position to support the market economy than private enterprises. Simultaneously, they are responsible for implementing national economic development strategies, creating sufficient jobs for the country, boosting national tax revenues, and stabilizing the economic order of the market. As such, we analyzed the double fixed-effects regression according to enterprises' ownership structures (Table 4). At 5% level, the coefficient for SOEs was 0.0838, which is significantly positive; for non-SOEs, it was not significant. Accordingly, the greater the degree of digital transformation of SOEs, the greater their technological potential.

Table 4 Analysis of heterogeneity regression results

	(1)	(2)	(3)	(4)
	TFP	TFP	TFP	TFP
	SOE	Non-SOE	Larger enterprises	SMEs
Tdodt	0.0838**	0.0271	0.0251	0.0652**
	(2.08)	(1.14)	(0.79)	(2.10)
TA	−0.457***	−0.402***	−0.440***	−0.378***
	(−13.26)	(−10.32)	(−11.55)	(−9.87)
OI	0.937***	0.975***	0.964***	0.915***
	(31.54)	(37.14)	(32.47)	(29.19)
DA	−0.0487***	−0.0607***	−0.0838***	−0.0376**
	(−3.04)	(−2.60)	(−3.91)	(−2.45)
AS	−0.647***	−0.748***	−0.508***	−0.627***
	(−7.81)	(−7.56)	(−5.05)	(−7.59)

BC	−0.0540	−0.209**	−0.00931	−0.303***
	(−0.61)	(−2.36)	(−0.09)	(−3.40)
IER	−0.364*	−0.380**	−0.338	−0.166
	(−1.94)	(−2.14)	(−1.48)	(−0.99)
TobinQ	−0.00990	−0.0327*	−0.0137	−0.0556***
	(−0.39)	(−1.74)	(−0.39)	(−2.83)
_cons	−2.232***	−3.830***	−2.614***	−3.486***
	(−4.38)	(−7.24)	(−3.99)	(−6.12)
N	679	470	611	523
F	163.0	267.1	156.1	141.9
r2	0.978	0.982	0.968	0.977

t statistics in parentheses

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

4.2.2. Enterprise size heterogeneity

The pace of technological advancement is influenced by the size of a company's digital transformation. Although large enterprises in heavily polluting industries have sufficient capital and strong risk resistance, traditional industrial structures and business models are difficult to completely innovate and transform quickly. As such, SMEs face fewer challenges when it comes to digital transformation than large enterprises, particularly in terms of HR optimization, radical changes in traditional industrial and supply chains, complex supply side optimization reforms, and declining customer stickiness, as larger enterprises are at the forefront of their industries, these barriers mean that many aspects of digital transformation may be overlooked. In contrast, for SMEs, the gap with large enterprises in terms of core industrial technology drives a greater willingness for digital transform and technological advancement. In addition, they have fewer departments involved in the digital transformation large enterprises. By investing in R&D, SMEs can achieve results quickly.

Based on the enterprise size of heavy pollution industries, quantify the heterogeneous effect of digital transformation on technological progress, we conduct double fixed- effects group regressions for large enterprises and according to the average value of their combined assets (Table 4). 0.051 is the regression coefficient for large enterprises, which is not significant; 0.0552 is the regression coefficient for SMEs, which is significantly positive at the 5% level. It is likely that SMEs are better able to make technological progress through digital transformation as the threshold for digital transformation is lower for them.

4.3. Robustness check

4.3.1. Explanatory variables replaced

Patents are often used to measure the novelty and inventiveness of a company's core technology. The study examined patent applications and invention patents filed by heavily polluting listed companies from 2000 to 2020 as a test of robustness. A total of patent applications was totaled, and the natural logarithm was taken to generate the indicator $Apply$. Based on enterprises' individual time two-factor fixed effects models, Table 5 shows the test results. It was found that coefficients $Tdodt$ were 0.230 and 0.177, which are both significantly positive at 5% and 10%, respectively. This confirms that digital transformation significantly promotes the technological advancement of heavily polluting industries, and further supports first hypothesis (H1).

Table 5 Robustness regression results

	(1) IApply	(2) Apply	(3) TFP	(4) TFP
Tdodt	0.230**	0.177*	0.0507***	0.0818**

	(2.11)	(1.74)	(2.87)	(2.36)
TA	0.169	0.104	−0.441***	−0.430***
	(1.38)	(0.91)	(−20.62)	(−11.05)
OI	0.207**	0.180*	0.954***	0.933***
	(2.10)	(1.94)	(55.67)	(30.24)
DA	−0.0435	0.0428	−0.0469***	−0.0671***
	(−0.70)	(0.73)	(−4.59)	(−3.14)
AS	−0.00341	0.113	−0.656***	−0.726***
	(−0.01)	(0.39)	(−12.10)	(−8.16)
BC	−0.154	0.00529	−0.133**	−0.0804
	(−0.50)	(0.02)	(−2.50)	(−0.90)
IER	−0.0932	−0.136	−0.197*	−0.0446
	(−0.14)	(−0.22)	(−1.71)	(−0.24)
TobinQ	0.0133	0.0419	−0.0201	−0.00227
	(0.17)	(0.58)	(−1.56)	(−0.10)
_cons	−5.212***	−4.269***	−2.921***	−2.340***
	(−3.10)	(−2.71)	(−9.89)	(−4.96)
N	1179	1179	1047	564
F	3.770	3.802	554.9	176.6
r2	0.820	0.834	0.987	0.984

t statistics in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.3.2. Changing the sample interval

Prior to 2010, emerging digital technologies were at an early stage and digital transformation had received little attention. 2010 was a watershed year in the development of digital transformation. In the aftermath of 2010, as the global economy grew and technology advanced, more and more emerging digital technologies were integrated into all aspects of social life; Furthermore, digital transformation is becoming a priority of corporate leadership for large companies and listed companies. We selected sample data from 2010-2020 to perform robustness testing (Table 5). The $Tdodt$ coefficient was 0.0507, this is a significant positive change at the 1% level, which is in line with the baseline regression results.

4.3.3. One period lagged explanatory variables

The process of digital transformation is often viewed as a continuous one; however, there may be a time effect on the impact of developments and innovations in digital technologies on an organization's technological progress. Table 5 tests the robustness of the baseline regression model using the explanatory variable 1 with one lag. The $Tdodt$ coefficient was 0.0818, H1 is further supported by the fact that digital transformation can significantly promote technological progress in heavy polluting industries.

5. Mechanism analysis

To test the second (H2), we took employee compensation payable as the threshold variable for regression analysis; A total of 300 samplings were conducted and single-threshold and double-threshold tests were performed (Table 6). At the 1% significance level, all single-threshold likelihood ratio test values were greater than the threshold value; this indicates a single-threshold effect. In addition, a double-threshold effect was also identified, with thresholds of 19.1782 and 23.4596. To further test whether the estimated values of the thresholds were equal to the true values, LR plots of the estimated values of the corresponding thresholds were plotted (Figure 1). The LR values were < 5% threshold and to 0; that is, the estimated thresholds were equal to the true thresholds, and the payables could be more accurately classified into three stages of payables (1) < 19.1782; (2) ≥19.1782 and < 23.4596; and (3) > 23.4596 (Table 7).

Table 6 Threshold tests

Threshold variables	Threshold	Threshold value	F-value	P-value
ERP	Single	19.1782	24.74	0.003
	Second	23.4596	12.49	0.060
R&D	Single	1.6800	25.06	0.000

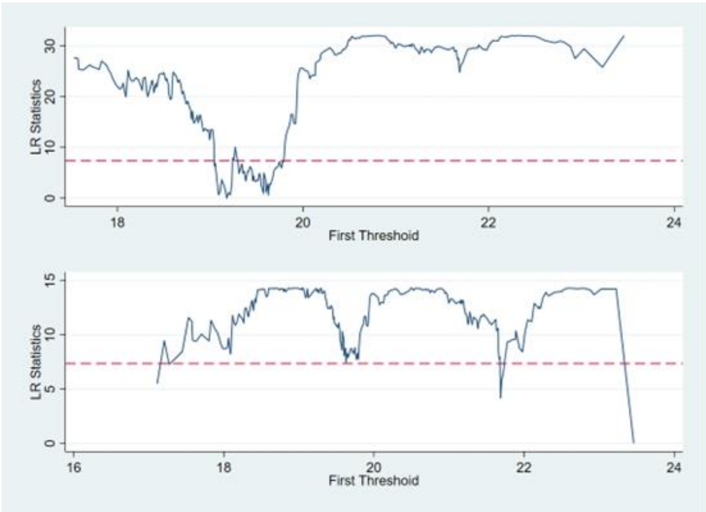

Fig1 . Trend in LR for double-threshold estimates.

The results of the threshold regression using payables as the threshold variable can be found in Table 7, when payables were <19.1782 and digital transformation was 0.102, the correlation between it and technological progress of heavily polluting industries passed the 1% significance threshold. When payables were ≥19.1782 and < 23.4596, There is a significant correlation between digital transformation and technological advance of heavily polluting industries, with a coefficient of 0.853 at the 1% level of significance. With a significance level of 1%, digital transformation had a coefficient of 0.853 for technological progress in heavily polluted industries; when remuneration payable to employees > 23.4956, Technology progress in heavily polluted industries was affected by digital transformation by 0.513, at 1%, the significance test is passed. Consequently, digital transformation impacts technological progress in heavy pollution industries in a nonlinear manner, with diminishing marginal effects; that is, digital transformation prompts the optimal deployment of HR within the enterprise, which accelerates the enterprise's technological progress. These findings confirm that the second hypothesis (H2) is correct.

Table 7 Threshold effect regression results

	(1) TFP	(2) TFP	(3) TFP
TA	−0.396***	−0.411***	−0.411***
	(−12.66)	(−9.13)	(−9.13)
OI	0.961***	0.982***	0.981***
	(47.80)	(31.07)	(30.97)
DA	−0.0304**	−0.0529**	−0.0530**
	(−2.32)	(−2.59)	(−2.59)
AS	−0.685***	−0.696***	−0.689***
	(−9.13)	(−5.65)	(−5.69)

BC	−0.00719	0.0340	0.0269
	(−0.13)	(0.39)	(0.32)
IER	−0.354**	−0.565***	−0.560***
	(−2.46)	(−2.80)	(−2.79)
TobinQ	−0.00347	0.00203	0.000624
	(−0.23)	(0.12)	(0.04)
0	0.129***	0.103***	0.102***
	(4.30)	(2.75)	(2.74)
1	0.0596***	0.0845***	0.0853***
	(2.63)	(3.03)	(3.01)
2			0.513***
			(6.37)
_cons	−4.527***	−4.268***	−4.246***
	(−8.09)	(−5.67)	(−5.61)
N	944	1179	1179
sigma_u	0.308	0.362	0.366
sigma_e	0.104	0.154	0.154
rho	0.897	0.847	0.850

t statistics in parentheses

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

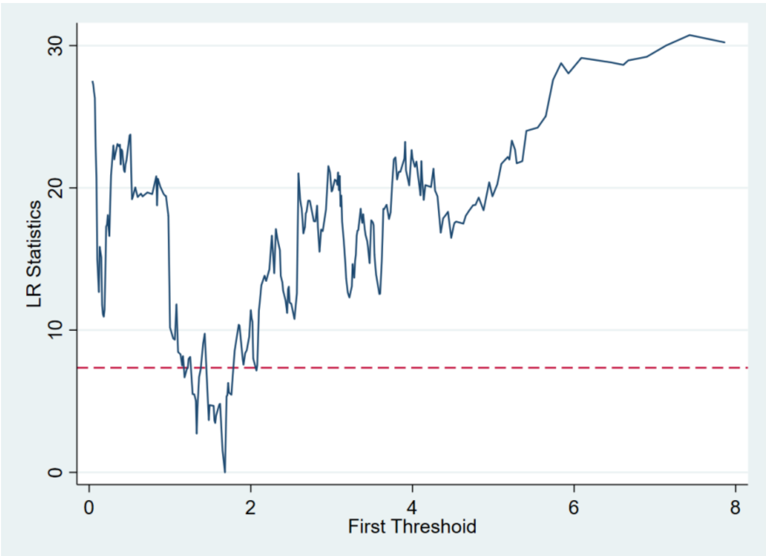

Fig2 . Trend in single-threshold estimates of LR

To test the third hypothesis (H3), the ratio between R&D investments and operating income is used as a threshold; A total of 300 samplings were conducted and single-threshold and double-threshold tests were performed (Table 7). It appears that a single-threshold effect exists since the likelihood ratio test values exceeded the critical value at 1% significance. On the other hand, no double threshold effect passed the significance test; there is no double threshold. We further tested whether the estimated threshold value matched the true value using LR plots of the threshold estimates (Figure 2). The single-threshold value was 1.6800, and the LR values fell below the 5% threshold and tended to be close to 0; that is, the estimated threshold was equal to the real threshold. A heavy polluting enterprise's R&D investment in its operating income can be completely divided into two phases: (1) ≤1.6800 and (2) > 1.6800.

According to the R&D investment to business revenue ratio of ≤1.6800, the coefficient of digital transformation on technological progress for the heavy pollution industry was 0.129, and at 1% significance level, the test passed. With a R&D investment to revenue ratio over 1.6880, in the heavy pollution industry, digital transformation impacted technical progress by 0.0596, passing the 1% significance test. It indicates that the impact of digital transformation on heavy pollution technology is non-linear and diminishing marginal; that is, through digital transformation, enterprises increase R&D investments, accelerating technological progress. These results show that the third hypothesis (H3) is correct.

6. Conclusion

Using a sample of listed heavy-polluting enterprises in China between 2001 and 2020, validating the impact of digital transformation on technological advancement. This empirical study suggests that digital transformation contributes significantly to technological development in enterprises. These findings hold even after conducting several robustness tests. In SMEs, SOEs, and companies that invest in R&D, heterogeneity analyses show that the relationships are more pronounced. Mechanism analyses show that increased investment in R&D, accelerates technological progress; in addition, digital transformation has prompted enterprises to optimize internal HR procedures and reduce management costs, accelerating their technological progress. Developing digital technology and pursuing the "dual-carbon" goal have combined to spur green innovation, which speeds up technological development. To promote green technological innovation, digital transformation can ease financial restrictions for corporations and attract more government support.

Policy implications abound when heavy-polluting enterprises transform digitally. Enterprises should take the first steps to raise awareness of digital transformation, strengthen the construction of data infrastructure, and integrate advanced digital technologies into their businesses; and enhance their and improve their digitalization level, in this way Promoting the technological advancement of enterprises.

Second, it is important for the government to increase financial support for digitally transformed businesses, reduce discrimination and constraints that exist in financial markets, especially for non-SOEs and medium-sized enterprises lacking capital, talent, and technology. As well as providing financial incentives for digital transformation, they should encourage such enterprises to innovate green technology, as well as improve the overall efficiency of this type of innovation.

Finally, financial institutions should reasonably provide financial support for SMEs and private enterprises to transform digitally promoting green technological innovation within enterprises.

In this study, digital transformation was measured based on text mining analysis. In the future, more accurate metrics should be identified; ideally, Quantifying the impact of a company's adoption of digital transformation technologies or specific dimensions of digital transformation would be useful.

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