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RESEARCH ARTICLE

The Impact of Enterprise Digitization on Green Total Factor Productivity: A Case Study of High-Polluting Companies in China

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ABSTRACT As an integral part of the digital economy era, the digital transformation of businesses can have a certain impact on their green total factor productivity, but causal identification of this impact remains limited. To address these shortcomings, this study selects 20 categories of heavily polluting enterprises based on the industry classification standards of the China Securities Regulatory Commission in 2012. Using listed company data from 2015 to 2019 and combining the global Malmquist-Luenberger productivity index, the study employs the Slacks Based Measure-Directional Distance Function model to assess the relationship between digitalization and green total factor productivity of enterprises. The research findings are as follows: 1) The promotion of digital transformation by businesses can significantly facilitate the improvement of green total factor productivity. 2) The results of the mediation effect test indicate that advanced digital technologies can enhance green total factor productivity by optimizing the internal financial conditions of enterprises. 3) Model construction demonstrates that market competition and investor sentiment play a moderating role in green total factor productivity. 4) Threshold regression analysis confirms that higher managerial capabilities enable the better digital transformation of enterprises, leading to higher green total factor productivity. Finally, from the perspective of enterprises themselves, this study proposes strategies to promote green total factor productivity and sustainable development. It expands the existing literature and evidence on the impact of digitalization on green total factor productivity while providing recommendations for businesses striving to achieve sustainable development.

INDEX TERMS Enterprise digital, financial situation market competition, investor sentiment, management ability, green total factor productivity.

I. INTRODUCTION

Global warming, resource scarcity, environmental pollution, carbon emissions, and climate change are all getting more and more problematic as the world economy grows [1], [2]. By erecting green trade obstacles and tightening environmental regulations, developed nations encourage the transfer of high-pollution businesses to developing nations [3]. Reflecting on China's 40-year development, it is evident that following the reform and opening up, a plethora of foreign industries was introduced into the country. In addition to causing serious environmental damage, this sector of the economy has accelerated China's economic growth. According to the research conducted by Kong et al., China's carbon emissions have shown exponential growth, increasing from 9.93 billion tons in 2020 to 11 billion tons in 2022. They also predict that this growth trend will continue in the next decade or so, possibly peaking in 2035 [4]. In addition, China has a serious issue with environmental pollution, which would inevitably cause economic growth to stall. Promoting China's green growth is a crucial issue since it highlights the conflict between energy, environmental, and economic concerns. The Chinese government is committed to shifting away from the development model that prioritized economic growth over

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environmental preservation. Environmental improvement is now a top priority for the government.

The digitization of enterprises is anticipated to drive China's economy to gradually shift from extensive development, focused on quantity and speed, towards an intensive development model that emphasizes green and quality [5]. Currently, the digital economy is flourishing, represented by new-generation information technologies such as big data analysis, cloud computing, mobile internet, artificial intelligence, and 5G. In response to this, China has introduced the "digital strong country" strategy to facilitate the digital technology revolution, with the digital economy serving as the most dynamic and potential new momentum. Thanks to the opportunity provided by the digital technology revolution, China's digitalization process is accelerating. Digitalization can leverage its digital information advantages to better integrate and merge physical manufacturing enterprises through information transformation, thus forming a data network among enterprises. This, in turn, reduces the cost of information search between enterprises and improves the survival cycle of physical enterprises [6], [7]. The question of how enterprise digitization affects green total factor productivity is a frontier issue worthy of study. China provides an excellent sample for research in this regard, primarily because of its digital economy, which ranks among the largest in the world. According to the "China Digital Economy Development White Paper (2021)," as of the end of 2020, the global digital economy had reached a scale of 32.6 trillion US dollars, accounting for 43.7% of GDP. China's digital economy scale is 5.4 trillion US dollars, second only to the United States. In light of this, the Chinese government attaches great importance to the digitalization process, stating that it will implement a new development concept, improve green total factor productivity, and guide the digital transformation of the real economy.

Environmental degradation and resource scarcity are two critical issues that are becoming increasingly urgent. To support sustainable economic development consistently, it is crucial to focus on resource and environmental factors and continuously improve green total factor productivity [8]. Traditional productivity measures often overlook negative environmental impacts on economic growth, resulting in ineffective productivity growth indicators [9]. In contrast, GTFP incorporates resource waste and environmental degradation caused by pollution into the measurement index [10]. Focusing on green total factor productivity can help achieve economic output goals while reducing climate change's effects in China [11]. Thus, it is essential for Chinese businesses to prioritize their GTFP to protect the environment and ensure ongoing production and operation. China's economic development is entering a new phase characterized by environmental pollution, fossil fuel shortages, declining worker productivity, and declining capital efficiency. Accelerating the shift in economic development mode and increasing resource allocation effectiveness are significant challenges. The digital economy has the potential to improve the efficiency of technological innovation, increase the competitiveness of products, encourage intelligent industry upgrading and transformation, provide inclusive digital financial services, encourage the wise use of resources, facilitate clean enterprise transformation, and increase productivity [12], [13].

Based on the aforementioned analysis, this study utilizes data from listed companies in China. By adopting the industry classification standards of the China Securities Regulatory Commission in 2012, it selects 20 categories of heavily polluting enterprises. By combining the GML index and employing the SBM-DDF model, the study calculates the impact of digitalization on green total factor productivity. The research findings indicate that the promotion of digital transformation by businesses can significantly enhance green total factor productivity. This conclusion holds true even after employing descriptive statistics, correlation analysis, benchmark regression, and robustness tests. Through mediation effect tests, we discover that, under unchanged conditions, advanced digital technologies can improve green total factor productivity by optimizing the internal financial conditions of enterprises. Furthermore, model construction confirms that market competition and investor sentiment play a moderating role in green total factor productivity. Lastly, threshold regression analysis reveals that the impact of digitalization on green total factor productivity is more significant in samples with stronger managerial capabilities. As managerial capabilities improve, businesses can better undergo digital transformation, leading to higher green total factor productivity.

The contributions of this study are primarily reflected in the following aspects:

Firstly, there is limited literature that calculates the relationship between digitalization and green total factor productivity of enterprises. This study explores the relationship between digitalization and green total factor productivity by selecting 20 categories of heavily polluting enterprises based on the industry classification standards of the China Securities Regulatory Commission in 2012. In contrast to existing research that mostly considers the green total factor productivity of enterprises from a macro perspective of digital economic development, this study analyzes it from the perspective of enterprise financial conditions, systematically examining the impact of digitalization on green total factor productivity and its underlying mechanisms. Therefore, the research findings of this study enrich the literature on green total factor productivity, provide empirical evidence from China, and explore the green value of enterprise digitalization. Secondly, this study employs the SBM-DDF model combined with the GML index to calculate the impact of digitalization on green total factor productivity. Different from other models, the combination of the GML index and the SBM-DDF model comprehensively addresses the research question, providing methodological innovation. Thirdly, it considers managerial capabilities as a threshold variable. The study finds that once managerial capabilities surpass the threshold, the impact of digitalization on green total factor productivity of enterprises increases. This expands the perspective for scholars in related fields to explore.

The structure of the remainder of this paper is as follows: Part II provides a literature review; Part III presents the theoretical analysis; Part IV elaborates on the research design; Part V conducts empirical research analysis and discusses our results; Part VI concludes the entire paper.

II. LITERATURE REVIEW

A. THE VARIABLES THAT AFFECT GREEN TOTAL FACTOR PRODUCTION

1) GREEN TOTAL FACTOR PRODUCTIVITY MEASUREMENT

Prior research have demonstrated that the conventional approach to measuring total factor productivity (TFP) only considers labor and capital inputs in relation to output, without accounting for negative externalities like pollution emissions and environmental degradation. This approach tends to overstate production efficiency and thus provides an inaccurate assessment of economic progress. In contrast, green total factor productivity (GTFP) incorporates both desired and undesired outputs, including environmental factors such as pollution emissions, making it more consistent with the current trend toward sustainable development [14]. Researchers have utilized both parametric and non-parametric methods to estimate GTFP. The former approach relies on stochastic frontier analysis (SFA), which measures the impact of random events on production behavior using a specific production function. However, the parametric method requires accurate assumptions and regulation of pricing information, function form, and other model requirements. Non-parametric methods, such as data envelopment analysis (DEA), do not have the same assumptions, but they fail to account for undesired output. To address this issue, researchers have integrated pollution emissions into the measurement framework of TFP using techniques such as the directional distance function (DDF) and the (ML) index [9]. Nonetheless, this approach can result in a "slack bias" when assuming proportional expansion and reduction of input and output variables. Tone developed a distance function (SBM-DDF) based on slack variables to mitigate measurement errors [15]. Oh developed the GML index established on the ML index, which is able to solve nonlinear problems without the need for linear programming [10]. This study employs the GML and SBM-DDF models to estimate firms' green total factor productivity. By doing so, the study aims to contribute to the current literature by utilizing robust methods that account for both desired and undesired outputs in the estimation of GTFP.

2) THE VARIABLES THAT AFFECT GREEN TOTAL FACTOR PRODUCTION

According to recent research by Zhang et al. [16], global green total factor productivity (GTFP) is influenced by three primary factors: technology, the economy, and government policies [17], [18], [19]. Various studies have focused on these areas, including technological advancement and technical efficiency, which are two subcategories of technology [20]. The Technical Progress Index and Technical Efficiency Index are components of GTFP that can be used to measure these subcategories [21], [22]. Technological progress is a primary driver of GTFP enhancement, and digital technology has been identified as a key factor that can promote long-term economic and societal growth [23]. Improving technical efficiency can lead to better production component combinations, industrial upgrading, and enhanced economic input-output efficiency. Conversely, poor technical efficiency and environmental management efficiency can negatively affect GTFP [24]. By optimizing these economic categories, policymakers and stakeholders can create a more sustainable economic environment while promoting economic development [25]. The relationship between GTFP and economic development follows a "U" shape, where initial rapid economic growth can lead to increased resource use and pollution [26], [27]. However, this is followed by improved resource efficiency and a cleaner, more efficient economic structure [28], [29]. According to Li and Gao and Lu et al., high marketization levels can promote the efficient utilization of national economic resources and facilitate the growth of the green economy [30], [31]. Government departments also play a role in promoting GTFP enhancement by encouraging businesses to adopt technological innovation and create green technologies through low to moderate environmental regulations. However, excessive governance costs can negatively affect GDP. The development of infrastructure has the potential to both positively and negatively impact GTFP [25]. While it can facilitate interregional contacts and raise marginal productivity, excessive infrastructure building can result in significant energy use, pollution, and a detrimental impact on GTFP [32]. Overall, these three areas are crucial for promoting GTFP enhancement, and further research is needed to explore their interactions and their respective contributions to GTFP. Furthermore, if the government were to implement comprehensive fiscal decentralization, it would significantly hinder the improvement of green total factor productivity, with this inhibitory effect being more pronounced in China's central and western regions [33].

B. GREEN TOTAL FACTOR PRODUCTIVITY AND THE DIGITAL ECONOMY

In 1996, Don Tapscott introduced the term "digital economy" in his book, and it was formally introduced in the US Department of Commerce's "Emerging Digital Economy" study in 1998 [34]. Since then, the digital economy has experienced remarkable growth and has become a significant force for promoting global economic recovery. However, there is significant variation in how the digital economy is measured and accounted for due to different definitions of the concept. Scholars interpret the digital economy and its associated indicators from different research perspectives. For example, Moroz et al. and Miloiev et al. have assessed the digital economy's development level from national and specific characteristic perspectives [35], [36]. Various techniques are used to measure the digital economy, including sampling calculations, curve fitting, tax capacity calculations [37], principal component analysis, and the entropy method. The impact of the digital economy has been evaluated at three primary levels: micro-firms, meso-industries, and the macro-economy. At the microenterprise level, the digital economy has been shown to increase business value [38]. At the corporate level, it enhances economic output and facilitates the transition of internal management paradigms [39], [40]. Industrial digitization is a practical means of boosting the manufacturing sector's competitiveness within the context of the digital economy [40]. The digital economy also has a significant impact on the social economy, permeating all aspects of the economy and society [41]. The macroeconomic benefits of the digital economy include increased productivity [42] and higher export quality [43].

China's "digital power" strategy and "green development" concept have made it imperative to comprehend the digital economy's impact on GTFP and its mode of operation. Recent research by Pan et al. has investigated the innovation-driven effect of the digital economy on China's TFP [25], revealing a sustainable extension of China's TFP. Other studies have indicated that the digital economy can influence China's green development and GTFP through enhancing technological efficiency and progress [44]. The digital economy's growth has ushered in new business models that incorporate green elements, including the platform and sharing economies [45]. The integration of the digital economy with the real economy can enhance production processes and accelerate digital transformation [46]. It is noteworthy that the measurement and accounting of the digital economy are highly variable, and its impact is evident at different levels, including microenterprise, corporate, and macroeconomic levels. Therefore, understanding the digital economy's precise impact on GTFP is crucial, especially given China's recent emphasis on "green development" and the "digital power" strategy.

In summary, previous studies have extensively explored the relationship between the digital economy and green total factor productivity, yielding insightful conclusions. However, there is limited research that examines the impact of corporate digitization on green total factor productivity and its underlying mechanisms from a micro-level perspective. Additionally, the consideration of managerial capabilities in this context is also scarce. Therefore, building upon prior research, this paper adopts a methodology that combines the GML index with the SBM-DDF model to systematically examine the impact and mechanisms of corporate digitization on green total factor productivity. Furthermore, by conducting threshold regression analysis on managerial capabilities, the relationship between corporate digitization and green total factor productivity is investigated.

III. THEORETICAL ANALYSIS

A. ENTERPRISE DIGITIZATION AND GREEN TOTAL FACTOR PRODUCTIVITY

With the increasingly serious global epidemic, the role of enterprise digital transformation in fostering Chinese enterprise development and economic growth has shown strong vitality and is developing into a significant force to mitigate the epidemic's effects and foster the steady recovery of China's economy. According to the "cost effect" theory, businesses that have gone digital can swiftly access information resources, lessen data distortion during information transmission, and lessen information asymmetry between suppliers and demanders, all of which lower transaction costs [46]. Through digital transformation, businesses can simultaneously attain a high level of supply chain and production chain integration, creating a "connection effect" [30]. According to the "competition effect" theory, businesses that go digital not only have better collaboration and production skills in their supply chains, but they also have quicker access to information. Additionally, orders from companies with lower production costs will inevitably rise significantly, which will ratchet up competition within the same sector, alter the way businesses innovate, and encourage pertinent companies to speed up technology research and development, boost production efficiency, and lower production costs [40]. Enterprises may be able to swiftly obtain cutting-edge technology and management experience thanks to the sharing features of business digitalization, which may also cause knowledge or technological spillovers throughout the sector and create a "demonstration effect" [47], [48]. Endogenous growth theory suggests that the accumulation of knowledge across society plays an essential part in facilitating the advancement of the economy. In this context, the digital transformation of businesses, especially the widespread adoption of the internet, has facilitated the sharing and exchange of human knowledge and information across time and space. As a result, it has become easier for people to acquire new knowledge and skills, contributing to the overall growth of society. The digital transformation of businesses can encourage the earliest possible matching of corporate and individual demand on the platform and increase matching effectiveness. Customers can easily and quickly find the best products and services. To encourage product innovation and actively participate in the company innovation process, consumers transition from passive to active participants [49]. The internal management processes of businesses have evolved and have been transformed by enterprise digital technology, which has also redefined the competition mode, competition mechanism, and competition border of businesses [50].

Enterprise digitization can effectively increase economic benefits by stimulating innovation efficiency, optimizing industrial structure, enhancing public service capability, and strengthening environmental supervision. It can also reduce production factor input, reduce environmental undesired output, and improve GTFP in the area where the enterprise is located, in addition to improving the TFP of the enterprise itself. The deep integration of digital technology and traditional businesses has significantly altered how they produce goods and services, organize their operations, and innovate technologically. This has also reduced the friction involved in business transactions, enabled the unrestricted dissemination of information and lowered the expenses associated with information provision [51]. Technology innovation is a significant role in fostering green total factor production, according to Pan et al. [25]. Through the integration and inventive development of conventional agriculture, industry, and service industries, digital transformation can integrate digital technology into all phases of production and circulation, pushing the upgrading of various industrial structures. The modernization of industrial structure significantly aids in fostering regional economic expansion and raises green total factor productivity [52]. Kunkel & Matthess draw the conclusion that as industrial production expands, so does the potential of digital transformation for environmental sustainability [53]. The rate of resource utilization has been further improved, ecological pollution has been effectively reduced, and green total factor productivity will surely progressively rise as a result of the enhancement of the industrial framework. Additionally, while promoting the growth of new green industries, some of these sectors are advantageous for lowering pollution emissions, maximizing resource use, and enhancing environmental quality generally, all of which help to elevate GTFP. Costa & Matias shown how a sustainable innovation ecosystem can be produced as a result of digital transformation [54]. Pasqualino also discovered that by reducing environmental strain, digital transformation can create a more resource-efficient economic structure [55]. The integration of key components of the environmental protection system and ecological information and data has been successfully achieved with the development of the national ''digital government'' initiative. This has led to the establishment of an environmental management information system that facilitates the acceleration of information flow and the removal of barriers in accessing ecological data. Information resources may be shared and used between people, businesses, and governments with ease. On the other hand, by putting a strong emphasis on digital technology, it will be easier to monitor ecological environments, predict their behavior, and establish early warning systems, which will help to advance green development. The research hypotheses listed below are suggested in light of the analyses just mentioned:

H1: The increase of GTFP can be considerably aided by businesses promoting digital transformation.

B. THE FINANCIAL SITUATION'S FUNCTION AS AN INTERMEDIARY

Through corporate digitalization, numerous assets within the company are combined with digital technology. Technology in the digital age is not a stand-alone emerging resource. It is typically integrated with the business's current human, financial, and material resources, considerably enhancing the effectiveness of internal organizational collaboration and providing the business with distinctive creative benefits [56]. The capacity to access more digital resources, such as a thorough supply chain management system, cutting-edge digital production processes, and potent sales clientele, is another benefit of high levels of digitization for businesses. These internal resources allow businesses to acquire useful information quickly and accurately, which lowers transaction costs [57]. Businesses tend to be better equipped to utilize information technology, enjoy it, and incorporate more resources the more digitally digitized they are. Therefore, in accordance with the theory of resource orchestration, digitization can enhance an organization's capacity for innovation, speed up the acquisition of information, make it easier for an organization to coordinate its various resources, allocate resources optimally, increase production efficiency, and ultimately enhance an organization's financial situation [58]. Moreover, digitization can inspire organizational change and motivate groups to actively take action to increase their competitive advantages, assisting businesses in achieving favorable financial conditions. The financial status of businesses can impact their green total factor productivity. For example, financial constraints may lead to changes in a company's financial situation, which could affect its level of green productivity [59]. According to a study by Chang and Tang, companies can integrate their digital development with the financial system to ease financing restrictions, improve their financial standing, and ultimately increase their green total factor productivity [60]. Another study by Aghion and Askenazy et al. suggests that digitalization can influence an organization's production process and organizational structure, resulting in cost reductions, improved operational efficiency, and optimized financial status [61]. Based on this research, it can be concluded that digitalization plays a crucial role in enhancing the GTFP of businesses.

H2: By maximizing an organization's internal financial situation, modern digital technology can raise total factor productivity while keeping all other factors constant.

C. RIVALRY IN THE MARKET'S MODERATING IMPACT

According to the theory of industrial organization, the market rivalry is a significant external factor that affects corporate strategy and decision-making. This theory also suggests that market rivalry has an external governance effect on companies. The theory of competitive advantage suggests that industries with intense competition have lower entry barriers, leaving businesses vulnerable to ''predation'' from potential newcomers or existing rivals. This reduces profit margins, increases liquidity risk, and raises the likelihood of bankruptcy. Consequently, businesses tend to prioritize short-term objectives over long-term benefits, which can lead to muted effects of digital transformation on green total factor productivity [62], [63]. However, the signal transmission theory suggests that actively upholding GTFP obligations can create a positive impression of a company and convey to outsiders that it is in good shape. This can increase stakeholder trust and position businesses to compete effectively in the market [64]. Drawing from the aforementioned analyses, the following research hypotheses are proposed:

H3: Market competitiveness regulates the influence of digital transformation on GTFP.

D. INVESTING SENTIMENT'S MODERATING IMPACT

According to the behavioral finance theory, investors' conduct will be influenced by emotions like psychological bias and may be illogical in their investing decisions [65]. This is mostly shown in: When investors are in a good mood, they always have high expectations for their investments and pay less attention to corporate information; however, when they are in a bad mood, they have low expectations for their investments and are cautious, so they pay more attention to corporate information. The poor choices made by the investors in this situation will hurt both their personal wealth and the efficiency of the market [66]. Also, as a result of the various operational and financial risks that businesses will face during their continuous life cycle, they will need to employ a variety of financing options. When investor confidence is high, it can make the external financing environment for businesses relatively loose and make it easier for businesses in various life cycles to raise money through the external environment for risk management and strategic adjustment. That is to say, under conditions of high investor sentiment, investors will be eager to invest in businesses, and businesses will have more funding for digital transformation in order to increase GTFP. The research hypotheses listed below are suggested in light of the analyses just mentioned:

H4: While all other factors remain constant, businesses with strong investor sentiment will experience an increase in their green total factor productivity.

E. THRESHOLD EFFECT OF MANAGERIAL ABILITY

Managerial aptitude is a thorough reflection of the knowledge, expertise, and worth of business managers. It serves as a gauge for how well business leaders can forecast industry growth trends based on their own expertise, manage their operations effectively, treat their workforce fairly, and increase their organizations' input-output ratios [67]. In general, the better the ability of enterprise managers, the more they should have a long-term perspective, the more they can make the best use of the limited resources available to them, and in the same financial situation, the better they will be able to utilize the advantages of enterprise digitization to increase the GTFP of their organizations. The research hypotheses listed below are suggested in light of the analyses just mentioned:

H5: An enterprise's digital transformation will be better and its GTFP will be greater the more capable the managers are.

IV. RESEARCH DESIGN

A. DATA SOURCES AND SAMPLE SELECTION

This study includes information from listed businesses in the heavy pollution industries of Shanghai and Shenzhen from 2015 to 2019. The primary sources of information, such as firm financial characteristics, are Wind, CSMAR, and CNRDS. This study examines the financial reports of publicly traded companies to analyze the intangible assets data and generate a digital transformation index. Prior research on this topic is consulted to inform the processing of the original data. These are the precise techniques: (1) The CSRC 2012 industry classification criteria selects 20 different categories of highly polluting firms. (2) ST, ∗ ST, and PT companies are designated for elimination for the sample period. (3) The aforementioned industry samples are removed due to the uniqueness of financial and insurance firms in the context of the sector. (4) Disregarding the observed figures for the IPO businesses from the corresponding year. (5) Remove information with blank values. (6) All continuous variables are tailed by the 1% and 99% quantiles to prevent outliers from compromising the reliability of regression.

B. EXPLAINED VARIABLE

1) VARIABLE BEING EXPLAINED

Total factor productivity is calculated using SBM-DEA in the neoclassical economic model from the perspectives of supply and output, and it has since evolved into a key indicator for gauging economic development [68]. It takes a certain amount of money and labor to compensate for and restore the ecological harm caused by environmental contamination. From this vantage point, the amount of economic development will be overestimated by the total factor productivity if environmental contamination is not taken into account [69]. Pollution should be considered an unwanted output when measuring production efficiency, according to the initial theory put forth by Chamberset et al., and the resulting GTFP can measure production efficiency more precisely [70].

Typically, scholars measure GTFP by utilizing labor, stock capital, and energy consumption as input variables, and regional GDP and pollution as output variables, often at the provincial or city level [71]. However, little attention has been given to examining GTFP at the organizational level. To address this gap, the present study adopts an approach proposed by Wang et al. [72], which (1) employs the number of employees at the end of the year as a labor input variable for computing GTFP, and (2) utilizes the following formula for calculation:

$$K_t = (1 - \delta) K_{t-1} + \frac{I_t}{P_t} \tag{1}$$

where K_t represents the capital stock in the period t, I_t represents the new fixed assets in the period t, and P_t is the fixed asset investment price index of the province. (3) Standard coal is utilized as the energy input variable for the enterprise's energy consumption, and the coefficient is the ratio

TABLE 1. Variable definition.

	Sign	Name	Measure
Variable being explained	*GTFP*	Green total factor productivity	The measurement method introduced above
Explanatory variables	*DGLR*	Enterprise Digitalization	The proportion of digitally related assets in intangible assets
	DGL		Combined with text analysis, the entropy method is used to calculate
Mediator variable	*ZScore*	Financial position	The financial risk model was proposed by Edward Altma (1968).
Regulated variable	*HHIB*	Market competition degree	Herfindahl index, describing the degree of competition in the industry
	IC	Investor sentiment	By decomposing TobinQ, we obtain
Threshold variable	*ME*	Managerial ability	Demerjian et al. (2012) proposed a method to measure managerial ability.
Control variables	*lev*	Asset-liability ratio	Liabilities/Assets
	roa	profitability	Net profit after tax / Total assets
	cash	Cash flow status	Operating cash flow / Total assets
	pat	Green patent	Citation of enterprise green patents
	top1	Ownership concentration	The proportion of major shareholders
	board	Board size	Natural logarithm of The number of board members
	stock	Institutional ownership	Institutional investors shareholding

of the enterprise's running costs to the industry's operating costs, multiplied by the industry's energy consumption as the enterprise's energy consumption. (4) The enterprise's commercial income as the anticipated production. (5) Similar to the enterprise energy measuring method, pollution produced by the enterprise is viewed as an undesirable outcome. The SBM-DDF model is used in conjunction with GML to assess the GTFP of businesses.

2) EXPLANATORY VARIABLES

Measuring an organization's level of digitization can be done in various ways, such as using text analysis and intangible assets. This study uses the proportion of year-end intangible assets related to digital transformation in publicly traded corporations' financial reports as a measure of their digitalization level. To calculate this measure, the study sums up the number of digital technology intangible assets, which are identified by their detailed items, including software, network, client, management system, and other keywords that pertain to digital transformation technology and related patents. This measure serves as a proxy for assessing the level of digital transformation within a business. The chosen detailed items were carefully verified to ensure the validity of the screening process. Additionally, a robustness test is performed using text analysis to determine the level of enterprise digitalization.

C. MODEL CONSTRUCTION

An empirical model (2) is created to evaluate the model to examine the impact of digital transformation on GTFP and hence test hypothesis 1. This is how the model is displayed.

$$GTFP_{i,t} = \alpha + \beta_1 DGLR_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{2}$$

The primary emphasis of this article is GTFP, and the primary explanatory variable *(DGLR)* is the degree of digitalization. *DGLR* is represented by the interaction term of group and time dummy variables. The controlling factor is control, $\sum firm$ effects firm individual fixed $\sum year$ control time fixed effects.

This study primarily focuses on the *DGLR* regression coefficient β_1 which shows how wage firms' levels of digitalization affect their overall factor productivity as a whole. Hypothesis *H1* of this paper is established if coefficient β_1 in the regression result is significantly positive. According to the study, companies with a high degree of digital transformation are more likely to see a substantial rise in *GTFP* when compared to those with lower levels of digital transformation.

To test the intervening effects of digital transformation on GTFP, the study develops models (3) and (4) based on model (2). The models use the internal financial status of enterprises, as measured by *ZScore*, to further investigate the influence of digital transformation on *GTFP*:

$$Zscore_{i,t} = \alpha + \beta_1 DGLR_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{3}$$

$$GTFP_{i,t} = \alpha + \beta_1 Zscore_{i,t} + \beta_2 DGLR_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{4}$$

The influence of digital transformation on *GTFP* varies depending on the level of market rivalry and the bias of investor sentiment, according to the prior theoretical analysis. Market competition and investor sentiment have moderating impacts on this influence. Based on this, model (5) is created using an interaction term to see if market competition and investor mood serve as a moderating factor on the effect of the digital transformation on *GTFP*:

$$GTFP_{i,t} = \alpha + \beta_1 HHIB_{i,t} * DGLR_{i,t} + \beta_2 DGLR_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{5}$$

V. EMPIRICAL STUDY

A. ADESCRIPTIVE STATISTICS

Table 2 displays the descriptive statistics for the present article. The median value of enterprise digitization (DGLR) is 0.0020, which is smaller than the average value, showing that a few firms with a high degree of digitization have increased the average value of data. The average value of enterprise digitization (DGLR) is 0.0270. The standard deviation of ZScore is 6.15, indicating substantial variability in each enterprise's financial standing. The financial health of the majority of

TABLE 2. Descriptive statistics.

Variable	N	SD	Mean	Min	p50	Max
GTFP	2,784	1.9608	0.4428	-4.8186	0.1285	10.0705
DGL	2,784	0.0103	0.0038	0.0000	0.0000	0.0000
DGLR	2,784	0.0873	0.0270	0.0000	0.0020	0.6666
ZScore	2,784	6.1484	4.8029	-0.0767	2.8784	40.2036
HHIB	2,784	0.0772	0.0720	0.0145	0.0500	1.0000
IC	2,784	1.4922	-0.0397	-2.3827	-0.3282	6.8562
lev	2,784	0.2053	0.4424	0.0563	0.4409	0.9079
roa	2,784	0.0653	0.0406	-0.1918	0.0348	0.2381
cash	2,784	0.0616	0.0458	-0.1376	0.0418	0.2249
pat	2,784	0.4007	0.0755	0.0000	0.0000	3.0000
top1	2,784	0.1548	0.3668	0.0108	0.3532	0.7622
board	8,547	0.2023	2.1756	1.6094	2.1972	2.7081
stock	8,547	0.2344	0.4772	0.0045	0.4984	0.9265

Chinese businesses is still solid, as shown by the ZScore's mean, median, and empirical values of 4.80, 2.88, and 3.27, respectively.

B. CORRELATION ANALYSIS

The correlations between the key factors examined in this study are presented in Table 3. It is evident that a noteworthy positive correlation exists between the degree of DGLR and GTFP.

In this study, we conducted an expansion factor test and the results have been presented in Table 4. All of the expansion factors are less than 10. There is no collinearity issue, according to an initial assessment. This study employs the fixed effects of individual and time through the Hausman test, which can partially address the endogenous issue brought on by group differences.

C. BENCHMARK REGRESSION

To verify the hypothesis H1 of this study, baseline regression analysis was conducted using Model (2). In the regression results, particular attention was given to the coefficient of the impact of the degree of enterprise digitalization (DGLR) on green total factor productivity (GTFP). The regression results are presented in Table 5. The test result is shown in Column (1) without any additional control variables. The results reveal a significant correlation between the degree of DGLR and GTFP at a level of significance of 10%, with a correlation coefficient of 0.827. Furthermore, column (2) displays the test results for finance-related control variables, including enterprise size, age, and cash flow [73]. Column (3) tests three control variables, namely ownership concentration, board size, and institutional shareholding percentage, which are associated with the characteristics of company management [74]. The test outcome after including the aforementioned control factors is shown in Column (4). The endogenous issues brought on by missing variables can be reduced by increasing the control variables. Table 5's results show that adding control variables enhanced the model's explanatory power (adj. R-sq), and the coefficient of the relationship between enterprise digitization degree (DGLR) and green total factor productivity (GTFP) varied between 0.783 and 0.843, both at a level of 10%. It demonstrates that, provided H1 is confirmed, firms' promotion of digital transformation can considerably support the improvement of GTFP.

D. ROBUSTNESS TEST

The robustness test is a series of tests to investigate and evaluate the reliability of conclusions, and its purpose is to ensure that the research conclusions do not change with alternative indicators and model transformation [75].

1) ENDOGENEITY TEST

The dependent variable and independent variables may have reverse causality, leading to endogenous problems. Selecting appropriate instrumental variables for dependent variables is efficient to alleviate endogeneity worrying. To tackle the endogeneity concern in this research, we utilized the two-stage least squares (2SLS) method in combination with the generalized method of moments (GMM) dynamic panel model to examine the endogeneity of the benchmark regression outcomes. The instrumental variable applied was the average DGLR of other firms in the region, following the method proposed by Li and Gao [30]. The findings are displayed in column (1) of Table 6. The results indicate a robust positive correlation between the predictor variable and the outcome variable. The endogenous test yielded a Kleibergen-Paap rk LM 1% with a P value of 0, Stock-Yogo 10% of 16.38, Kleibergen-Paap rk Wald F of 217.347, and there was no weak instrumental variable. To investigate potential causal relationships between the degree of enterprise digitization and the GTFP of businesses, we delayed the degree of enterprise digitization by one order, and Column (2) of Table 6 displays the findings. As observed, the independent variable and the dependent variable demonstrate a strong positive association. The endogenous test yielded a Kleibergen-Paap rk LM 1% with a P value of 0, Stock-Yogo 10% of 16.38, Kleibergen-Paap rk Wald F of 37.419, and there was no weak instrumental variable.

2) REPLACE EXPLANATORY VARIABLES

This study also employs a new approach to measuring intangible assets for businesses. We employed text analysis on the financial reports of listed firms to identify the frequency of words related to artificial intelligence, blockchain, cloud computing, big data, and digital technology applications, in order to measure the degree of digitization. To test the robustness of the results, we also used the entropy method. The regression findings in column (3) of Table 6 confirm the primary test and indicate that the DGL regression coefficient is statistically significant at a 10% level.

TABLE 3. Correlation analysis.

	GTFP	*DGL*	*DGLR*	*ZScore*	*HHIB*	*IC*	*lev*	*Roa*	*Cash*	*Pat*	*Top1*	*Board*	*Stock*
GTFP	1												
DGL	0.0310***	1											
DGLR	0.0140*	0.1620***	1										
ZScore	0.0210*	0	0.009	1									
HHIB	0	-0.036***	0.065***	-0.086***	1								
IC	0.0560***	0.093***	0.044***	0.393***	0.032***	1							
lev	-0.0250**	-0.063***	-0.007	-0.603***	0.110***	-0.037***	1						
roa	0.0840***	0.012	0.005	0.354***	-0.034***	0.297***	-0.435***	1					
cash	-0.0305***	-0.022**	0.011	0.156***	0.013	0.103***	-0.153***	0.306***	1				
pat	-0.0207**	-0.028***	0.004	-0.057***	0.106***	0.040***	0.079***	-0.012	0.015	1			
top1	-0.0580***	-0.033***	0.034***	-0.076***	0.201***	0.059***	0.041***	0.112***	0.092***	0.099***	1		
board	-0.0420***	-0.072***	-0.016	-0.154***	0.133***	0.014	0.219***	0.006	0.037***	0.096***	0.037***	1	
stock	-0.0210*	-0.021*	0.021*	-0.078***	0.225***	0.131***	0.186***	0.108***	0.109***	0.115***	0.472***	0.256***	1

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

TABLE 4. Expansion factor.

Variable	VIF	1/VIF
stock	1.45	0.687344
roa	1.38	0.722273
lev	1.38	0.724451
top1	1.31	0.762253
board	1.13	0.886884
cash	1.11	0.897402
pat	1.02	0.976201
DGLR	1.00	0.998298
Mean VIF	1.22	

TABLE 5. Baseline regression.

	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP
DGLR	0.827* [0.4481]	0.783* [0.4343]	0.843* [0.4471]	0.805* [0.4351]
account	no	yes	no	yes
manage	no	no	yes	yes
firm	yes	yes	yes	yes
year	yes	yes	yes	yes
_cons	0.7460*** [0.0811]	-0.0289 [0.1463]	1.4450*** [0.5267]	1.0140* [0.5362]
N	8,547	8,547	8,547	8,547
adj. R-sq	0.1749	0.2009	0.1762	0.2013

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

E. THE INTERMEDIARY ROLE OF THE FINANCIAL SITUATION

The mediating effect test is shown in Table 7. The internal financial status index (ZScore) chosen for this study is a negative index, meaning that the worse the ZScore number, the worse the enterprise's financial situation. The internal financial position mediating impact tests are shown in Table 7's columns (2) and (3). (ZScore). An enhanced level of enterprise digitization has a notable impact on the internal financial position, as evidenced by the regression findings in Column (2) of the table, which indicate a significant coefficient of 2.404 for the variable ZScore at the 10% significance level. Column (3) of the regression findings shows that the coefficient of the internal financial situation (ZScore) is 0.792, which is significant at a 10% level. These results indicate that the degree of digitalization (DGLR) and green total factor productivity (GTFP) relationship is partially mediated by the enterprise's internal financial health (ZScore). Therefore, assuming H2 is validated.

TABLE 6. Robustness test.

	(1) GTFP	(2) GTFP	(3) GTFP
DGLR	15.93*** [2.4313]	23.83*** [6.6290]	
DGL			6.5200* [3.5189]
account	yes	yes	yes
manage	yes	yes	yes
firm	yes	yes	yes
year	yes	yes	yes
_cons			1.0700** [0.5350]
Kleibergen-Paap rk LM 1%	0	0	
Kleibergen-Paap rk Wald F	217.347	37.419	
Stock-Yogo 10%	16.38	16.38	
adj. R-sq	8,547	8,547	8,547
N	-0.3209	-0.5999	0.2013

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

F. THE MODERATING IMPACT OF INVESTOR SENTIMENT AND MARKET COMPETITION

The moderating effects test results are presented in Table 8. The base regression shows a significantly positive coefficient.

TABLE 7. Mediating effect.

	(1) GTFP	(2) Zscore	(3) GTFP
Zscore			0.0146** [0.0068]
DGLR	0.8050* [0.4351]	2.4040* [1.3449]	0.7920* [0.4483]
account	yes	yes	yes
manage	yes	yes	yes
firm	yes	yes	yes
year	yes	yes	yes
_cons	1.0140* [0.5362]	4.9610*** [0.2179]	0.6740*** [0.0900]
N	8,547	8,547	8,547
adj. R-sq	0.2013	0.0575	0.1756

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

TABLE 8. Regulatory effect.

	(1) GTFP	(2) GTFP
*HHIB*DGLR*	-5.280* [2.7208]	
*IC*DGLR*		-0.2210* [0.1347]
DGLR	1.224** [0.5613]	0.8650* [0.4533]
HHIB	2.1870*** [0.8291]	
IC		0.1160*** [0.0264]
account	yes	yes
manage	yes	yes
firm	yes	yes
year	yes	yes
_cons	0.8420 [0.5345]	1.1390** [0.5356]
N	8,547	8,547
adj. R-sq	0.2024	0.2036

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

The findings demonstrate that greater market competition hinders the relationship between digitization and GTFP, as evidenced by the significant coefficient on the cross-product term HHIBDGLR (-5.280) in column (1) of Table 8. Similarly, higher investor sentiment acts as a deterrent to the relationship between digitization and GTFP, as shown by the significant coefficient on the cross-product term ICDGLR (-0.221*) in column (2) of Table 8 at a 10% level of significance. These results provide support for hypothesis H3 and H4.

G. EFFECT OF MANAGERIAL SKILL AT A THRESHOLD

In this study, we investigate how the qualitative change of managerial ability (ME) can enhance the impact of GTFP through the degree of enterprise digitization (DGLR). We use the threshold regression approach and consider managerial ability (ME) as the threshold variable for GTFP. Table 9 presents the results assuming that the level of enterprise digitization (DGLR) is the threshold variable. The findings reveal a single threshold effect when managerial ability (ME) is utilized as the threshold variable.

TABLE 9. Threshold test.

Threshold	RSS	MSE	Fstat	Threshold value
Single	595.7870	0.0782	398.22	0.1682*
Double	590.0229	0.0775	74.39	-0.0407

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

TABLE 10. Threshold regression.

	GTFP ME<0.1682	ME>0.1682
DGLR	0.8820** [0.4073]	3.2380*** [0.5996]
account	yes	
manage	yes	
firm	yes	
year	yes	
_cons	1.7890*** [0.4861]	
N	8,547	
adj. R-sq	0.115	

Standard errors in brackets * p<0.1, ** p<0.05, *** p<0.01

The findings of the threshold regression test with managerial ability (ME) as the threshold variable are presented in Table 10. The results indicate that when the management ability (ME) exceeds 0.1682, it has a significant positive effect on GTFP. The coefficient increases significantly from 0.882 to 3.238, suggesting a significant improvement in productivity. These results provide support for hypothesis H5.

VI. DISCUSSION

With the development of the global economy, trade between China and other countries has been increasing, leading to the influx of foreign industries into China. While this has accelerated China's economic growth, it has also resulted in severe environmental pollution, prompting the country to take a series of measures for achieving sustainable development. Consequently, green total factor productivity (GTFP) has attracted significant attention and discussion among scholars. Previous research has addressed issues related to technological progress, economic development, environmental regulations, and government control, but they have overlooked the impact of enterprise digitalization on GTFP. This study selects 20 categories of heavily polluting enterprises based on the industry classification standards of the China Securities Regulatory Commission (CSRC) in 2012 and employs the SBM-DDF model in conjunction with the GML index to estimate the effect of enterprise digitalization on GTFP. Building upon the traditional DEA model, this study employs the SBM-DDF model, which possesses stronger transferability and globality, combined with the GML index to measure GTFP. The empirical results contribute to the existing literature on the relationship between enterprise digitalization and GTFP, providing insights into the digital transformation and sustainable development of Chinese enterprises. Furthermore, the findings assist scholars in understanding the perplexities surrounding the relationship between enterprise digitalization and GTFP from the perspectives of financial conditions, market competition, investor sentiment, and managerial capabilities.

Based on the relevant data of Chinese listed companies from 2015 to 2019, the research findings indicate that companies with good financial conditions tend to have higher GTFP, while market competition and investor sentiment also have an impact on a firm's GTFP. Although policymakers of enterprises may consider improving their financial conditions to enhance their GTFP, they often overlook the influence of market competition and investor sentiment. This is because most policy implementers primarily focus on direct benefits when implementing different policies, seldom considering indirect effects. Additionally, the results also demonstrate that higher managerial capabilities enable better digital transformation, leading to higher GTFP for enterprises. It suggests that policymakers in enterprises should introduce and cultivate more competent managers to comprehensively enhance the management level and GTFP of the enterprise. In addition to the requirements for enterprise policymakers, the government should also put more effort into policy-making, such as implementing policies tailored to local conditions to regulate market competition and mobilize investor sentiment, thereby enhancing the GTFP of enterprises and facilitating higher-quality development of the Chinese economy.

Similar to previous research, this study has certain limitations. Firstly, the measurement and selection of variables in this paper may not be precise and comprehensive, which may introduce some biases and affect the research results. Secondly, there may be limitations in the sample selection. On one hand, this study selects 20 heavily polluting enterprises based on the industry classification standards of the CSRC in 2012, but many non-listed companies are not included in the research sample, which may introduce certain sample limitations. In future research, if relevant data becomes available, we will strive to address the limitations. Lastly, other models such as Super-SBM and GML index method can also be used to estimate the GTFP of enterprises, providing new perspectives for future research in this field [76].

VII. CONCLUSION

After the release of the "China Digital Economy Development White Paper (2021)", the attention and sensitivity of various stakeholders towards the digital economy have increased. However, there is limited existing literature on the relationship between the digital economy, corporate digitization, and green total factor productivity. This paper focuses on the green value of corporate digitization and empirically examines the impact of corporate digitization on green total factor productivity by selecting 20 heavily polluting enterprises based on the industry classification standards of the China Securities Regulatory Commission (CSRC) in 2012.

The research findings of this paper are as follows: 1) The promotion of digital transformation by enterprises can significantly enhance green total factor productivity, a conclusion that holds even after employing descriptive statistics, correlation analysis, benchmark regression, and robustness tests. 2) Under unchanged conditions, advanced digital technologies can improve green total factor productivity by optimizing the internal financial situation of enterprises. 3) Market competition and investor sentiment play a moderating role in green total factor productivity, as demonstrated through model construction. 4) Threshold regression analysis reveals that the impact of corporate digitization on green total factor productivity is more significant in samples with higher managerial capabilities. The higher the managerial capabilities, the better the ability of enterprises to undergo digital transformation, resulting in higher green total factor productivity. These conclusions demonstrate that the impact of digitization on green total factor productivity remains valid from different perspectives. The research findings contribute to the discussion on the relationship between corporate digitization and green total factor productivity, providing empirical evidence from China and exploring the green value of corporate digitization.

The research conclusions also provide clear recommendations for enterprises: 1) As the digital economy gradually becomes a key force in reshaping global competitive patterns, the high-quality development of enterprises relies on the contribution of digitization. Enterprises should seize the new opportunities of the digital era, increase research and investment in digital technologies and infrastructure, actively promote their digital transformation, strengthen the deep integration of digital technologies with the physical economy, continuously improve their level of digitization, cultivate new driving forces for green development in China, and enhance green total factor productivity. 2) Enterprises should organically integrate digital technologies with various internal resources, such as human, financial, and material resources, to significantly improve internal organizational efficiency. Leveraging the advantages of information technology, enterprises should enhance their innovation capabilities, accelerate information acquisition, enjoy and integrate more resources, coordinate and optimize the allocation of internal resources, improve production efficiency, ultimately optimize the financial situation of enterprises, and further enhance green total factor productivity. 3) The government should further improve the policy support system for corporate digitization transformation. On one hand, it should accelerate the construction of digital infrastructure, guide enterprises to strengthen digital thinking and promote the digital transformation of industries. On the other hand, it should introduce corresponding policies to adjust market competition levels and mobilize investor sentiment, thereby enhancing green total factor productivity and facilitating higher-quality economic development in China. 4) Enterprises should introduce and cultivate more competent management talents to efficiently utilize digital technologies, help achieve deeper integration of digitization and enterprise development, and fully leverage the economic effects of digital technologies, thereby comprehensively improving management capabilities and green total factor productivity.

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