sustainability

MDPI

Article

The Impact of the Digital Economy on Industrial Eco-Efficiency in the Yangtze River Delta (YRD) Urban Agglomeration

Wenjing Zhang [1], Bin Sun [2,*], Zaijun Li [1] and Suleman Sarwar [3]

1 School of Business, Yangzhou University, Yangzhou 225127, China; mx120221203@stu.yzu.edu.cn (W.Z.)
2 School of Economics, Dongbei University of Finance & Economics, Dalian 116025, China
3 Finance and Economics Department, College of Business, University of Jeddah, Jeddah 21959, Saudi Arabia; ch.sulemansarwar@gmail.com
* Correspondence: 15776296660@163.com

Abstract: Enhancing industrial eco-efficiency (IEE) represents an inherent imperative in the pursuit of green, low-carbon, and high-quality development. The burgeoning digital economy (DE) contributes to the digitization and intelligent integration and transformation of production and consumption, which contributes to enhancing economic efficiency and resource utilization efficiency while reducing carbon emissions and the environmental pollution associated with industrial production and providing important support for the ecological transformation of industries. In this context, using data from the YRD urban agglomeration and employing the Tobit model and the spatio-temporal correlation model, this study analyzes the impact of the digital economy on industrial eco-efficiency. The findings are as follows: (1) The correlation over time between IEE and the DE followed an inverted V-shaped trend, while the relationship between the DE and pure technical efficiency (PTE) exhibited a fluctuating W-shaped pattern. The spatial correlation revealed Zhejiang province as the primary concentration of positive correlation between the DE and both IEE and PTE. (2) The development of the DE had a significant positive impact on IEE, not only directly but also indirectly through promoting green technological innovation and advancing industrial structure. (3) The analysis of regional heterogeneity showed that the development of the DE in core cities played a catalytic role in improving IEE, whereas the impact of the DE on IEE was not significant in outer cities. This research not only offers new views on how to develop industry in more environmentally friendly ways, but it also sheds light on the real effects of the digital economy on high-quality urban development.

Keywords: digital economy; industrial eco-efficiency; spatio-temporal association; the YRD urban agglomeration

check for updates

Citation: Zhang, W.; Sun, B.; Li, Z.; Sarwar, S. The Impact of the Digital Economy on Industrial Eco-Efficiency in the Yangtze River Delta (YRD) Urban Agglomeration. *Sustainability* **2023**, *15*, 12328. https://doi.org/10.3390/su151612328

Academic Editor: Luigi Aldieri

Received: 17 July 2023
Revised: 10 August 2023
Accepted: 10 August 2023
Published: 13 August 2023

1. Introduction

Rapid industrialization in China caused environmental problems such as high consumption, emissions, and pollution, challenging the push for high-quality development through resource-saving and environment-friendly modes [1–3]. To transition to a green and sustainable development path, rapid reforms were necessary. Policies like the Plan for Green Industrial Development (2016–2020) and the 14th Five-Year Plan for Green Industrial Development aimed to make industry more intelligent, green, and integrated, building a complete, advanced, and safe modern industrial system. To achieve these goals, essential improvements included green and low-carbon innovation, promotion of advanced cleaner production technologies, pollutant emission reduction, energy consumption reduction, and efficiency in resource utilization [4,5]. Additionally, the extensive utilization of digital technologies such as artificial intelligence, big data, and the Internet of Things (IoT) rapidly emerged as a significant catalyst for industrial upgrading, energy conservation, pollution reduction, and sustainable development. This transformative trend played a crucial role in fostering high-end, intelligent, and environmentally friendly advancements in manufacturing and constructing a modern industrial system [6,7]. Therefore, integrating the transformation of industrial digitization with industrial ecological goals was essential in achieving coordinated emission reduction, green expansion, and circular growth.

Digital economy has been a hot issue in the economic field. The early literature mainly favored the exploration of digital economy development index measurement and spatial distribution [8]. With the development of research, scholars have begun to focus on the economic effects resulting from the development of the digital economy. From a macro perspective, the existing literature mainly focuses on exploring the impact of the digital economy on the development of the green economy and the high-quality development of urban economy [9,10]. As for the micro level, the existing literature mainly focuses on the impacts on firm productivity and the upgrading of firms' position in the global value chain [11,12]. It is evident that existing studies have not yet focused on the role of digital economy in industrial eco-efficiency. Therefore, this paper explores how the digital economy affects industrial eco-efficiency.

In this study, the Yangtze River Delta region is used as a research sample. The YRD region is recognized as one of China's fastest changing and most developed city clusters, with a thriving digital economy and industries. The region has fostered a new generation of information technology industrial systems, featuring electronic products, information communication, integrated circuits, and other industries as the mainstay. In 2020, the YRD's digital economy accounted for about 44% of its regional GDP and 28% of the nation's total digital economy, with digital industrialization accounting for 26% and industrial digitalization accounting for 74%. Despite possessing a robust industrial foundation in new industries, traditional industrial development in the YRD region still faced multifaceted challenges such as low value-added production, low energy utilization efficiency, insufficient pollution control regulations, and other obstacles. This study firstly explored the correlation pattern between the DE and IEE, then examined whether digital transformation could catalyze improvements in IEE and identified underlying transmission mechanisms, and finally explored ways to integrate the digital economy to improve industrial eco-efficiency.

This paper is structured as follows: Section 2 presents the literature related to the research topic; Section 3 presents the theoretical analysis; Section 4 presents the methodology and data sources; Section 5 presents analysis of the results; and Section 6 presents the conclusions and discussion. Finally, Section 7 presents policy suggestions and the limitations of this study.

2. Literature Review

2.1. The Connotation and Evaluation of the Digital Economy

Despite the fact that the digital economy has permeated various aspects of our daily lives, there is still a lack of consensus regarding its precise definition. This is due in part to the constantly evolving nature of technology and its impact on economic activities. Moreover, the digital economy encompasses a wide range of sectors and industries, including e-commerce, digital communications, online entertainment, and financial services, among others [13]. From an economic form perspective, the digital economy is considered as the third main economic form, following the agricultural and industrial economies. It is characterized by data resources being the key component, contemporary information networks serving as the primary carrier, integrated applications of information and communication technology, and all-factor digital transformation serving as a significant driving force [14]. Planning for the digital economy aims to advocate for a new, more effective, and fairer type of economic system. Meanwhile, from the perspective of economic activities, the digital economy is comprised of a range of economic activities that rely on network information and communication technology [15]. With the advancement of information technology, "Internet+", and big data, the definition of the digital economy has steadily broadened. At the G20 Hangzhou Summit in 2016, the digital economy was described as a digital economy composed of a series of economic activities that use digital information and knowledge as key core production factors, modern basic information network as the carrier, and effectively utilize information and communication technology (ICT) as an important driving force to improve efficiency and optimize economic structure [16].

The digital economy comprises various key components and industries. According to [17], the main components of the digital economy include e-commerce, information technology, ICT infrastructure and transmission, communications, and the computer industry. These areas highlight the crucial role that modern technological innovations play in driving economic growth, promoting efficiency, and supporting sustainable development. On the other hand, Ref. [18] defines the industrial scope of the digital economy to encompass a range of sectors such as digital product manufacturing, digital product services, digital technology application, digital factor driving services, and digital efficiency improvement services. This emphasizes the diverse nature of economic activities associated with the digital revolution, including the creation of digital products and services, using cutting-edge technologies to transform traditional industries, and developing innovative business models that leverage digital capabilities. The development of the digital economy is generally measured through the construction of an index system and by using entropy weight and factor analysis to evaluate the measurement. The construction of an index system involves selecting a set of indicators that reflect the various aspects of digital economy development, such as the number of internet users, e-commerce sales, and broadband penetration. These indicators are then assigned weights based on their relative importance and combined into a composite index. This enables researchers to obtain a comprehensive overview of the level of digital economy and compare it across different regions and time periods [19–21]. This approach provides an objective and quantitative basis for measuring the size and growth rate of the digital economy, supporting evidence-based policymaking and decision making [22].

2.2. The Impact of the Digital Economy on Economic Development

The widespread adoption of digital technologies has made the DE a critical driver of innovation, productivity, and competitiveness. Consequently, it has created numerous employment opportunities and contributed to sustainable economic development. Additionally, the economic utility of the digital economy extends beyond traditional industries and sectors as it has the potential to create new business models, income streams, and jobs while promoting economic diversity. Furthermore, the digital economy facilitates geographical connectivity while improving business efficiency, supporting entrepreneurship, and stimulating innovation on a large scale [23,24]. Another aspect of the digital economy's utility is its potential for green solutions, enabling sustainable development and reducing carbon emissions. By facilitating remote work and e-commerce, the digital economy reduces the need for physical commuting and transportation, which leads to lower energy consumption and greenhouse gas emissions. Furthermore, the use of data analytics and artificial intelligence in smart energy management can optimize energy usage and reduce waste, further contributing to environmental sustainability [25–27]. Although the DE has brought many positive benefits, it is essential to recognize that it also poses potential negative environmental impacts. For instance, discarded electronic devices lead to electronic waste that can be hazardous if not properly disposed of, while the growing energy demands from data centers contribute to climate change [28,29].

2.3. Research on Industrial Eco-Efficiency

Eco-efficiency aims to maximize economic benefits while minimizing environmental impacts [30]. Improving IEE has the potential to establish a virtuous cycle between economic development and environmental protection, leading to the sustainable use of resources and environmental development, which in turn contributes to mitigating the negative impact of production processes on the environment and improving companies' competitiveness and economic benefits. Moreover, higher levels of IEE provide long-term support for economic growth [31]. Generally, the nonparametric data envelopment analysis (DEA) technique had been used to flexibly handle multiple inputs and outputs in measuring eco-efficiency [32]. However, the original DEA model had limitations in addressing undesired output and indistinguishable efficiency ranks of decision-making units (DMUs). To overcome these issues, researchers developed the super-efficiency slacks-based measure (Super-SBM) model [33,34]. This model was more appropriate for evaluating IEE as it considered both environmental performance and industrial productivity under environmental constraints [35]. Furthermore, it could be further decomposed into PTE and SE. Related research has shown that IEE is influenced by multiple socioeconomic factors, including technological level, resource utilization efficiency, pollution control, management level, policy support, and industry structure [36,37]. These factors are interdependent and collectively impact the improvement of IEE.

2.4. The Impact of the Digital Economy on Industrial Production

There is a lack of research on the relationship between the DE and IEE. However, some recent studies have shed light on this issue. Firstly, from the perspective of industrial analysis, the Internet has been found to promote high-quality industrial development by facilitating scientific and technological innovation [38,39]. It has also contributed to industrial green growth by driving development while using novel and sustainable energy sources [40,41]. Secondly, attention has been paid to the impact of the DE on carbon emissions, industrial SO_2 emissions, and urban air quality [42–44]. For instance, it has been discovered that there exists an inverse U-shaped relationship between the growth of the DE and environmental pollutant emissions [45,46]. In addition, the manufacturing sector's carbon efficiency is significantly affected by the digital economy in a U-shaped nonlinear pattern [47]. Lastly, the development of the DE has had positive effects on local air quality, leading to incentives for reducing air pollution in nearby cities [48–50].

To summarize, while there are numerous studies on the definition and measurement of the digital economy, as well as the indicators, influencing factors, and measurement methods of IEE, research on the relationship between the two is currently limited. However, exploring this relationship is crucial for achieving sustainable and high-quality industrial development. Therefore, this study aims to address this issue as follows. Firstly, there is currently no research that explores the spatio-temporal association between the DE and IEE. Secondly, this study will study the direct impact and underlying mechanisms of the DE on IEE from the perspective of urban agglomerations. Finally, a heterogeneity analysis will be conducted to enable the development of differentiated implementation strategies.

3. Theoretical Analysis and Hypotheses

As traditional businesses increasingly seek to transform themselves into intelligent entities, digital technology has emerged as a critical tool for achieving this goal. Through the innovative application of advanced techniques such as big data analysis, artificial intelligence, and digital control systems, businesses can significantly improve their efficiency, reduce costs, and achieve greater environmental sustainability. Firstly, digital technology has become an indispensable tool for businesses seeking to transform themselves into intelligent entities in the age of big data. By leveraging advanced information retrieval, collection, analysis, and evaluation techniques, companies can make informed decisions about investing in green engineering projects that are both environmentally beneficial and cost-effective. Moreover, by implementing cutting-edge digital technologies like artificial intelligence and digital control systems throughout their production chain, businesses can enhance their productivity by accurately monitoring and adjusting their production processes in real time. Secondly, digital platforms also offer a powerful network for enterprise production. By breaking down geographic barriers and facilitating information sharing across supply chains, digital platforms enable businesses to efficiently match supply and demand goals, lowering transaction costs and optimizing factor allocation [51]. In addition, digital technology provides powerful tools for environmental management, enabling companies to monitor waste and pollution emissions in real time and adjust their operations accordingly. Thirdly, one of the key advantages of using big data technology is its ability to help businesses stay attuned to market trends and consumer preferences in real time. With swift access to market information, companies can modify their production schedules to meet customer demand more effectively, boosting their competitiveness in the marketplace [9]. Therefore, the first hypothesis is given as:

Hypothesis 1. *The development of DE will promote the improvement of IEE.*

Based on the logic that DE drives high-quality development, there may be two indirect mechanisms to promote the improvement of IEE. Given the ongoing promotion of high-quality development goals in an environment where resources are scarce, businesses are recognizing the pressing need to adopt sustainable and environmentally friendly practices. In this context, green technology innovation has emerged as a key pathway for industrial enterprises to address negative environmental externalities and promote eco-friendliness. From a macro perspective, the digitalization of the economy is driving information technology innovation and creating new sectors while fostering a pool of highly skilled talent. By accumulating superior human capital, knowledge flow and diffusion can be facilitated, leading to the generation of innovative ideas and concepts. This creates positive externalities and accelerates the pace of green technology innovation aimed at achieving sustainable development. In addition to accelerating green technology innovation, the growth of digitalization also improves information transmission efficiency. With the integration of resources from various regions, digitalization breaks time and space constraints on resource flow, enabling data sharing between regions at a lower marginal cost [52]. This enhances the efficiency of information transmission, spurring new business opportunities and facilitating more rapid development. Moreover, digitalization enables businesses to take advantage of technology spillover effects, leading to greater innovation returns [53]. Businesses can share knowledge and expertise with other entities, enhancing their own ability to innovate while contributing to the advancement of the industry as a whole.

Hypothesis 2. *Through increased innovation in green technologies, the digital economy can indirectly help to increase industrial production efficiency.*

The digital economy, far from being a direct substitute for traditional growth, plays a crucial role in fostering the evolution and transformation of the industrial structure through several key mechanisms [54]. It stimulates new industries and business models by promoting innovation while simultaneously sustaining and enhancing existing markets and industries. Furthermore, big data and artificial-intelligence-supported high-end technologies create synergies and diffusion effects with traditional industries in the digital economy [55], encouraging the continuous growth of added value and leading to breakthroughs in the progressive advancement of industrial structure development [56]. In addition, digital technology can be integrated into every stage of production within the digital economy, facilitating the free flow and efficient distribution of resources, optimizing resource utilization, and increasing industry correlation to promote coordinated development across various sectors [57]. The fundamental competitiveness of an industry during the industrial upgrading process is rooted in its cutting-edge scientific and technical capabilities and R&D innovation. By increasing R&D investments, businesses can encourage technological, process, and product innovation, reduce their dependence on energy and raw materials, maintain their market leadership, and promote green development. Lastly, the optimization of industrial structure can enhance resource utilization efficiency and achieve green development by fostering specialized cooperation, refining the industrial division of labor, and facilitating the transition of production factors from low-efficiency to high-efficiency sectors [56]. Therefore, the third hypothesis is given as:

Hypothesis 3. *By promoting industrial upgrading, the digital economy can have a favorable indirect effect on industrial eco-efficiency as well.*

4. Data and Methodology

4.1. Methodology

4.1.1. Spatio-Temporal Grey Incidence Model

Although the problem of "insufficient valid data and incomplete information" existed in traditional mathematical statistical analysis, grey incidence analysis was adept at handling uncertainty caused by multi-factor impacts with "partially known information". However, traditional grey models only considered a single object or a single time dimension, and they could not address the problem of different grey correlation rankings in panel data. To tackle this issue, constructing a spatio-temporal panel grey incidence model and introducing incremental differences was further proposed [58]. In the temporal dimension, the model utilized the development level of incremental representation indicators, and in the object dimension, it incorporated the distribution characteristics of deviation representation indicators [59,60]. By extracting relative differences in the developmental levels and directions of different indicators across dimensions, their correlation sizes and polarity were measured. A grey index correlation model based on exponential functions was constructed to more accurately grasp the spatio-temporal trend coefficient between digital economy development and industrial eco-efficiency.

4.1.2. Panel Tobit Model

In this paper, the value of industrial eco-efficiency calculated by the super-efficiency SBM-Undesirable model based on DEA was a restricted variable. Direct adoption of least square regression would have resulted in significant errors. To address the truncated problem of the dependent variable, the Tobit model was employed; the maximum likelihood estimation (MLE) method was utilized to estimate the parameters and was a more appropriate choice for obtaining more precise results [61]. The panel Tobit model was expressed as follows:

$$Y_{it} = \alpha_{it} + \beta^T X_{it} + \varepsilon_{it}$$
$$Y_{it} = \begin{cases} Y^*_{it}, & if\ Y^*_{it} < 1 \\ 1, & if\ Y^*_{it} \geq 1 \end{cases} \tag{1}$$

where Y_{it} was the calculated industrial eco-efficiency measured with a latent variable Y^*_{it}. X_{it} was the independent variable vector. β^T was the estimated regression coefficient. a_{it} was the intercept vector. ε_{it} was the random disturbance term.

4.2. Data Sources

Due to the multiple inputs and outputs involved in evaluating industrial eco-efficiency, this study selected several input indicators, including industrial electricity consumption, industrial land area, industrial employees, and industrial water consumption, based on the availability of data and indicator selection proposed by [59,60]. Additionally, both undesirable and desirable outputs were considered, with the industrial added value chosen as the target output and deflated to 2011 equivalents using the price deflator. The discharge of industrial wastewater, waste gas and smoke emission, and solid dust waste discharge were selected as the undesirable outputs. Then, the MaxDea Ultra 9.1 software was employed to compute the super efficiency values for IEE, PTE, and SE for each city from 2011 to 2020 [62].

As there was still no unified evaluation index system for the DE, this study constructed an evaluation index based on relevant research by [40,63]. The evaluation index comprised four dimensions, namely, digital economic infrastructure, digital economic industrial scale, digital economic innovation capability, and digital inclusive finance, to comprehensively reflect digital economy development (Table 1). The weight of each selected indicator was determined using the entropy weight method [64]. Subsequently, the weighted comprehensive value was obtained. The raw data for the indicators corresponding to the first three dimensions are available from the China Urban Statistical Yearbook (2012–2021). For the digital inclusive finance index, the data come from the Digital Finance Research Center of Peking University.

Table 1. The evaluation index for DE.

Primary Index	Second Index	Specific Indicator	Weight
Digital economy development index	Digital economic infrastructure	Internet broadband users per 10,000 people	0.0505
		Mobile phone users per 10,000 people	0.0384
	Digital economic industrial development	The proportion of employees in the information transmission, computer services, and software industry to the total number of employees	0.1473
		Per capita telcom revenue	0.4100
	Digital economic innovation	Number of patent applications for seven key digital economy industries	0.0366
	Digital inclusive finance	Digital inclusive finance index	0.3172

To minimize biased estimation caused by variable missing, this study also selected the following four control variables to more accurately evaluate the impact of the DE on IEE. First, it is noteworthy that regions with low economic levels usually ignore environmental costs during industrial development, resulting in severe environmental damage from using inefficient, high-energy-consumption, and high-pollution production methods. In contrast, regions with high economic levels tend to have a higher technology level, stronger environmental awareness, and a more scientific use of resources. They pay greater attention to environmental costs and ecological benefits during industrial development, adopting efficient, low-energy-consumption, and low-pollution production modes, which positively promote environmental protection. Per capita GDP (PGDP) was used as a proxy for measuring the level of economic development.

Second, the impact of population density on IEE has two opposing effects. On the one hand, higher population density could result in more environmental pressure and resource shortages, potentially having a negative impact on industrial ecological efficiency. On the other hand, regions with high population density tend to concentrate more talent and technological resources, leading to greater innovation activity, which can promote economic development, improve technological innovation capability, and enhance resource utilization efficiency. Furthermore, regions with high population densities can overcome environmental challenges through rational planning and management to achieve sustainable development, thereby improving industrial eco-efficiency. The number of people per unit area was used to reflect population density (PD).

Third, the impact of urbanization on IEE is complex and involves various effects, including the population density effect, scale effect, and agglomeration effect. Firstly, urbanization leads to the aggregation of people, promoting economic activities and social interaction. This facilitates resource sharing and optimization of supply chains, and stimulates technological innovation and experience-sharing, thereby improving industrial eco-efficiency. Nevertheless, high population density can also have detrimental effects, such as traffic congestion, noise pollution, air pollution, etc., negatively affecting industrial eco-efficiency. Furthermore, urbanization enables industrial enterprises to take full advantage of the scale effect, reducing production costs. As the size of an enterprise increases, they can invest more funds in research and development and technological improvement, thus promoting technological progress and improving industrial eco-efficiency. However, the scale effect can also bring forth large-scale environmental pollution problems that could potentially negatively affect industrial eco-efficiency. Additionally, urbanization helps enterprises form industrial clusters, promoting exchange and cooperation among enterprises, research institutes, and universities, while facilitating technological innovation and experience sharing, and improving economic benefits and ecological efficiency. The urbanization rate was characterized by the proportion of the urban population to the total population (URB).

Fourth, foreign direct investment has a dual impact on IEE. On the one hand, foreign companies and well-known brands are attracted through FDI, promoting technological innovation and industrial upgrading while also helping to improve the industrial ecological environment. Additionally, foreign investment brings resources such as funds, talent, and management experience which lead to optimized industrial structure and improved ecological benefits. On the other hand, FDI can also have negative impacts on the local environment. Foreign-invested enterprises might prioritize short-term profits over environmental protection and social responsibility. Such behavior might result in the wastage of local industrial resources and environmental pollution, ultimately leading to further environmental degradation and ecological deterioration. The ratio of urban foreign direct investment to GDP was used to measure the development level of foreign investment (FDI).

According to the research hypothesis, both green technology innovation and the upgrading of industrial structure were selected as the intermediate variables. The level of green innovation (GI) was measured by summing the number of green utility model patent applications and green invention patent applications The upgrading of industrial structure (UIS) was calculated through the weighted product of the proportion relationship between industries and the labor productivity of each industry.

To ensure the availability and completeness of research data while mitigating the potential impact of fluctuations induced by the COVID-19 outbreak on results, the research period was limited to the years between 2011 and 2020. All related statistical data were sourced from various publications, including the *Jiangsu Statistical Yearbook* (2012–2021), the *Shanghai Statistical Yearbook* (2012–2021), the *Zhejiang Statistical Yearbook* (2012–2021), the *Anhui Statistical Yearbook* (2012–2021), the *China Urban Statistical Yearbook* (2012–2021), and the *Statistical Bulletins of National Economic and Social Development* for each city during 2011–2020. To mitigate the effects of inflation, relevant economic data, such as GDP, were adjusted and converted using 2011 as the base year.

5. Analysis of Results

5.1. The Spatio-Temporal Incidence Pattern between IEE, PTE, SE, and DE

Before calculating the correlation coefficients between the DE and IEE, SE, and PTE, the indicators for each city were preprocessed using the logarithmic operator. Then, Excel was used to calculate the correlation of the preprocessed data. Finally, the results were visualized by ArcGIS 10.8 software, and the results are presented in Figures 1 and 2. Figure 1 illustrates the temporal correlation intensity between the DE and IEE, exhibiting an inverted V-shaped variation trend. The correlation coefficient showed a continuous increase from 0.408 in 2011 to 0.544 in 2015, followed by a gradual decline, reaching 0.359 in 2020. This suggests that the impact of the DE on IEE was initially strengthening and subsequently weakened over time. Similarly, the correlation intensity between the DE and PTE displayed a W-shaped fluctuation trend. The correlation coefficient between the DE and SE demonstrated a similar pattern to the relationship between the DE and IEE, exhibiting an inverted V-shaped fluctuation trend. These findings indicate that improvements in IEE were closely related to the changes in SE.

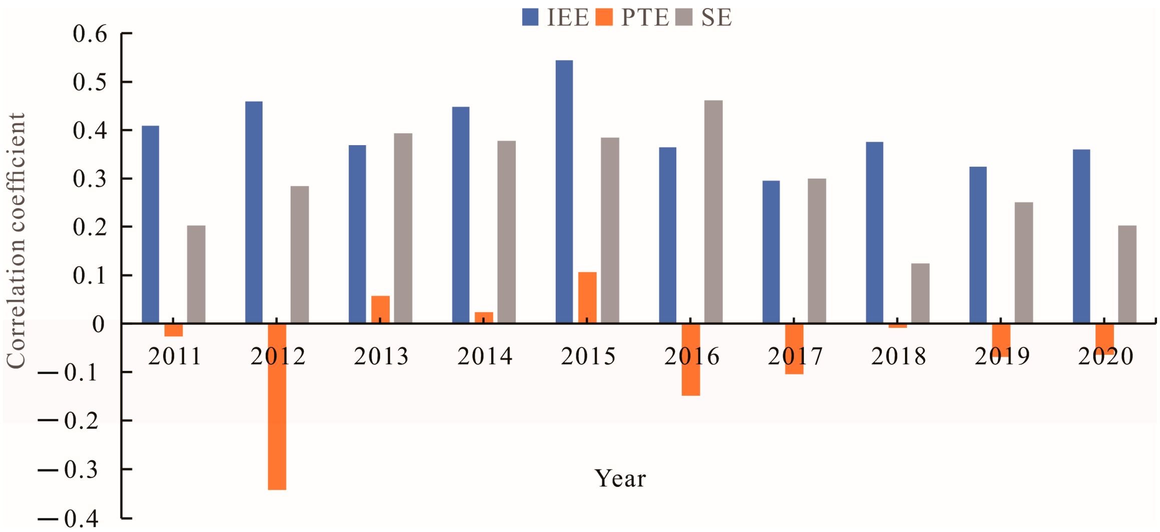

Figure 1. The temporal correlation trend between the DE and IEE, PTE, and SE.

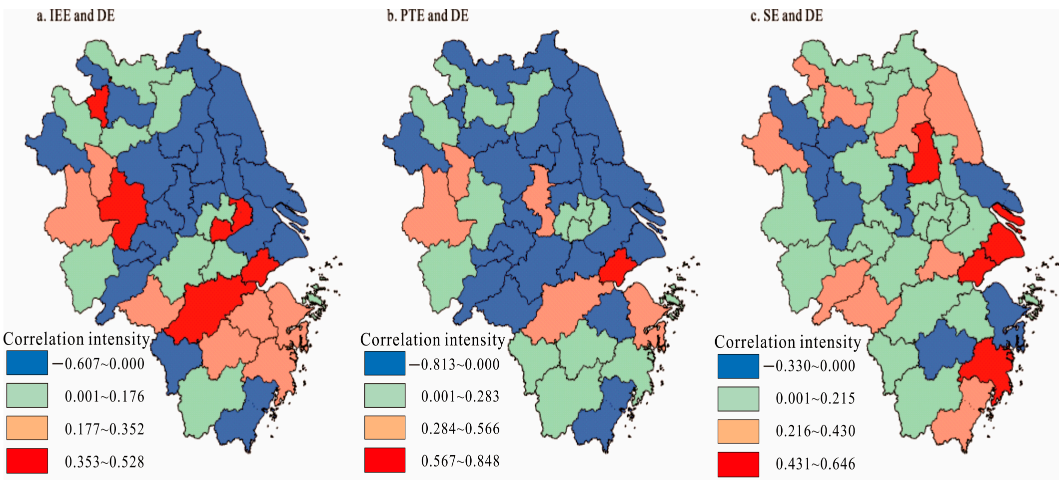

Figure 2. Spatial correlation pattern between the DE and IEE, PTE, and SE.

The spatial correlation coefficient was categorized into four intervals: below 0, and three equal intervals from 0 to the maximum values of 0.528, 0.848, and 0.646, respectively. As shown in Figure 2, 46.34% of cities exhibited a negative correlation between the DE and IEE, primarily distributed in Anhui and Jiangsu provinces, where the development of the DE has been significantly affected by the absence of high-quality Internet enterprise resources and a shortage of highly skilled professionals. These factors had a substantial impact in impeding the growth of the digital economy. Furthermore, cities such as Fuyang, Suzhou, Ma'anshan, Taizhou, and Yancheng have failed to transform their industrial production and continue to develop a large number of labor-intensive and low-end industries. This makes it challenging for digital technology to penetrate all areas of industrial green development. Positive correlation cities accounted for 53.66% of the total, mainly concentrated in most of the cities in Zhejiang province and some cities in Anhui province. A high correlation city such as Hangzhou, as a representative city of the digital economy, attracts more enterprises related to the digital economy through the Internet innovation and entrepreneurship system represented by Alibaba Enterprises, the Zhejiang Business Department, the Overseas Returnees Department, and Zhejiang University, greatly driving the development of the digital economy in the neighboring cities, as well as providing a broader employment space. Enterprises can create intelligent manufacturing systems to automate and intelligently control industrial production with the use of technologies like big data and cloud computing. Such efforts will improve environmental protection, energy conservation, and operational efficiency.

The spatial correlation analysis revealed distinct patterns in the relationship between the DE and PTE. The southern part of the delta region exhibited a stronger spatial correlation intensity, while the central and northern parts displayed a comparatively weaker pattern. In terms of the distribution of cities, those with a negative correlation accounted for 56.1%, whereas positive correlation cities constituted 43.9% of the total. This shows that most urban industrial firms struggle to fully integrate digital technology with industrial research and development, green manufacturing, and pollution control. The proportion of cities with negative correlation between the DE and SE was 19.51% and primarily clustered in Anhui province, with scattered locations in Jiangsu and Zhejiang provinces. Negative correlations were found in cities such as Bozhou, Huainan, and Bengbu, where industrial enterprises are small and have a long-term reliance on capital-driven growth. In the context of the development of the digital economy, these industries are unable to make the capital inputs and highly skilled personnel investments required by digital technologies, leading to a mismatch between production methods and factor structures, which inhibits industrial-scale production. Cities with a positive correlation accounted for 80.49% of the total, predominantly concentrated in Jiangsu, Zhejiang, and the central part of Anhui province.

5.2. The Direct Impact of DE on IEE

Before conducting the regression analysis, unit root tests including the LLC, IPS, and ADF-Fisher tests were employed to assess the stationarity assumption of each variable during the research period (Table 2). The results of these tests confirmed that all variables met the requirement of stationarity throughout the study. Based on the theoretical analysis above, DE can have a direct impact on IEE, as shown in Table 3. The first column included no control variables, and the regression coefficient was 1.390, which was significant at the 1% level of statistical significance. After adding all the control variables in the second column, the coefficient for digital economy dropped to 0.663. However, it still passed the 1% level of statistical significance test. Furthermore, the Tobit test results in the third column showed that the regression coefficient passed the 10% level of statistical significance with a value of 0.271. This demonstrated that DE continued to have a favorable impact on IEE. Hypothesis 1 was supported by the evidence. IEE has indeed benefited from the DE. Digital technologies had enabled businesses to optimize their production processes and reduce waste and pollution emissions, thereby promoting greater environmental sustainability. By providing powerful tools for information retrieval, collection, analysis, and evaluation, digital technology had also helped businesses make more informed decisions about investing in green engineering projects that are both environmentally beneficial and cost-effective. Moreover, digital platforms had created powerful networks for enterprise production, enabling businesses to break down geographic barriers and efficiently match supply and demand goals, lowering transaction costs and optimizing factor allocation. Thus, the DE had played a crucial role in promoting IEE, leading to greater environmental sustainability and economic prosperity.

Table 2. Results of unit root test.

Variable	LLC Test		IPS Test		ADF-Fisher	
	Z Value	***p* Value**	**Z Value**	***p* Value**	**Z Value**	***p* Value**
IEE	−11.922	0.000	−6.646	0.000	−6.695	0.000
DE	−11.065	0.000	−3.802	0.000	−27.204	0.000
URB	−5.850	0.000	−44.022	0.000	−3.618	0.000
PGDP	−4.280	0.000	−19.694	0.000	−4.038	0.000
PD	−13.276	0.000	−8.386	0.000	−12.773	0.000
FDI	−14.604	0.000	−13.713	0.000	−8.372	0.000

Table 3. Results of the impact of DE on IEE.

	Panel Model	Panel Model	Tobit Model
DE	1.390 *** (6.58)	0.663 *** (4.23)	0.271 * (1.95)
URB		−0.425 *** (−4.07)	−0.199 * (−1.87)
PD		0.069 *** (3.11)	0.037 (1.58)
PGDP		0.228 *** (5.86)	0.122 *** (3.17)
FDI		0.062 *** (6.36)	0.080 *** (8.29)
N	410	410	410
R^2	0.2382	0.420	

Note: The significance levels indicated by ***, and * are 1%, and 10%, respectively, with the T values in parentheses.

According to the results of the regression analysis with control variables, the level of urbanization had a negative impact on IEE. The Yangtze River Delta region faced challenges such as unbalanced and insufficient urbanization, where regions with high development levels did not play a leading role, and there was an unequal distribution of resources. Consequently, industrial green development was inversely connected with the urbanization of the Yangtze River Delta. In terms of PD, excessive density could lead to resource shortages, increased pollutant emissions, and other issues that negatively impacted the efficiency of green industries. Conversely, moderate population density could provide more labor and market opportunities for businesses and promote the development of green industries. Regarding economic development, different levels of economic development across regions could also impact the efficiency of green industries. Developed areas are typically better able to leverage modern technologies and green economic concepts to promote the development of green industries, while underdeveloped areas lack relevant technology and experience, hindering the full realization of the efficiency of green industries. To address these issues, the Yangtze River Delta region has closely adhered to the path of high-quality green development. The government has implemented various policies, businesses have expanded their investments in green technology, and public awareness of green environmental protection has progressively grown, which has been extremely helpful in fostering the growth of green industries. These efforts have greatly promoted the green development of industry in the region. Moreover, the coefficient of FDI was notably positive. The Yangtze River Delta region attracted more foreign investment, which facilitated the delivery of cutting-edge green technology and gave businesses access to more productive, secure, and environmentally friendly methods.

5.3. The Indirect Impact of DE on IEE

Based on the preceding theoretical analysis, we utilized a mediation effect model to examine whether the application of GI and the improvement of UIS through the use of the DE could affect IEE, as shown Table 4. As indicated in Table 4, the regression analysis uncovered a significant influence coefficient of the DE on the level of GI, with a coefficient of 1.496 that passed the 1% significance test. This finding suggested that the DE effectively contributed to the enhancement of GI. Additionally, column 2 provided empirical evidence supporting the notion that the improvement of GI acted as a valuable intermediary mechanism through which the DE could enhance IEE. This can be attributed to the YRD region's provision of ample developmental prospects and implementation of robust talent attraction policies, which facilitated the accumulation of human resources for the advancement of green technologies. Furthermore, the YRD region demonstrated a strong emphasis on achieving high-quality development and achieved notable progress in the realm of the digital economy, thereby fostering an increased awareness among enterprises regarding green production practices. Moreover, the coefficient related to the

DE in column 3 passed the significance test at the 1% level, indicating its positive role in UIS. Additionally, the findings presented in column 4 demonstrated UIS as another intermediary factor contributing to the relationship between the DE and improved IEE.

Table 4. Results of mediation effect regression.

	GI	IEE	UIS	IEE
DE	1.496 *** (5.76)	0.413 ** (2.53)	0.379 *** (6.28)	0.571 * (1.75)
GI		0.511 *** (7.63)		
UIS				1.864 *** (2.59)
Control variables	Yes	Yes	Yes	Yes
N	410	410	410	410
R^2	0.6882	0.4428	0.6892	0.4354

Note: The significance levels indicated by ***, **, and * are 1%, 5%, and 10%, respectively, with the T values in parentheses.

5.4. Robustness Test

Although this paper included some control variables, it was important to acknowledge that the accuracy of the results may have been influenced by unpredictable factors. To ensure the robustness of the findings, two methods were employed. In the first robustness test, the regression analysis was repeated while excluding municipalities and provincial capitals from the sample. As municipalities and provincial capitals generally possess better economic conditions and have a greater capacity to attract high-quality talent, their inclusion might introduce certain biases. The results, presented in the second column of Table 5, demonstrated that even after removing these areas from the analysis, although the coefficient size of the DE may vary, it remained significantly positive. Furthermore, the explained variable was adjusted in the second robustness test. PTE and SE were used as alternative explained variables for the robustness test. The results, depicted in columns 2 and 3, confirmed that even after changing the explained variables, the significance tests were passed and a positive effect was observed.

Table 5. The results of the robustness tests.

	Exclude Municipalities and Provincial Capitals	PTE	SE
DE	0.885 ** (2.24)	0.311 * (1.77)	0.552 ** (2.00)
Control variables	Yes	Yes	Yes
N	370	410	410
R^2	0.377	0.217	0.757

Note: The significance levels indicated by **, and * are 5%, and 10%, respectively, with the T values in parentheses.

5.5. Spatial Heterogeneity Analysis

Geographical location, economic development level, policy implementation impact, industrial historical base, and development degree indeed varied among cities in the YRD region. In order to more closely examine the effects of the DE on IEE within this context, a heterogeneity analysis was conducted by dividing the YRD cities into core and non-core categories. The specific results of this analysis are presented in Table 6. For cities located in the core areas, the coefficient of the DE on the development of IEE was significant, passing the significance test at the 1% level. However, for non-core cities, the coefficient was not significant. There were several factors that may explain these differences. Firstly, core cities typically had a higher concentration of scientific research universities. This fostered collaborations between the government, enterprises, and universities, creating an environment conducive to knowledge exchange, innovation, and technological advancements. The active cooperation and support from these key stakeholders resulted in increased financial resources allocated to the development of the digital economy. Consequently, core cities were more likely to have a higher level of digital economic development compared to non-core cities. Secondly, core cities in the YRD region typically exhibited more advanced industrialization systems and a higher degree of industrialization. This superior industrial base served as a solid foundation for the adoption of digital technologies and the implementation of green transformation strategies. Core cities were well-equipped to integrate digital innovations seamlessly into their existing industrial processes, thereby enabling them to optimize resource utilization, enhance production efficiency, and promote eco-friendly practices. Moreover, the higher degree of industrialization in core cities created internal pressures and incentives for green transformation. To enhance market competitiveness and sustainability, enterprises in core cities actively invested in improving their green innovation capabilities. This proactive approach towards green practices drove the development of high-quality industries that prioritize eco-efficiency and environmental sustainability.

Table 6. Results of spatial heterogeneity.

Variables	Core Cities	Non-Core Cities
DE	0.881 *** (4.45)	−0.896 (−1.35)
Control variables	Yes	Yes
N	270	140
R^2	0.372	0.141

Note: The significance level indicated by *** is 1%, with the T values in parentheses.

On the other hand, compared to core cities, non-core cities have several shortcomings. Firstly, the industrial foundations of non-core cities were relatively weak, and the sources of funds were insufficient. The integration of the digital economy and industrial development is a multifaceted systematic project, with not only the need for a large amount of capital investment in the early stage, but also a transformation process that is a long cycle, resulting in slow outcomes. As a result, high costs constrain the willingness of industrial enterprises to engage in digital transformation. Secondly, the level of technology and the talent pool were limited, so the digital transformation of industry in non-core regions was not sufficiently resourced. There are large gaps in China's digital technology talent, the traditional talent resource system can hardly meet the existing demand, the development space is limited, and the attraction of high-quality talent is insufficient, therefore resulting in the digital transformation of enterprises being thwarted. Thus, these cities' IEE was not significantly influenced by the DE.

Considering these factors, it became evident why the influence of the DE on IEE was more pronounced in core cities compared to non-core cities in the YRD region. The unique characteristics and strengths of core cities provided them with advantages in leveraging the benefits of the digital economy for sustainable industrial development.

5.6. Endogeneity Test

The issue of missing variables was prioritized due to the potential causal relationship between the growth of the DE and IEE, which could have led to inconsistent estimation findings. In this study, the instrumental variable approach was employed, utilizing the two-stage least squares method. The instrumental variable chosen was the number of telephone sets at the end of 1984. From a technical background and usage patterns perspective, it was believed that the development of local telecommunications infrastructure had an impact on the subsequent application of Internet technology. This instrumental variable satisfied the relevance criteria as it was logically associated with the focal variables. Furthermore, this selected instrumental variable consisted of historical data, having no direct relationship with IEE, thus meeting the exclusivity condition required for instrumental variable analysis. As indicated in column 2 of Table 7, the validity of the instrumental variable was confirmed by an F-statistic greater than 10, refuting the weak instrumental variable test. The results from the second stage regression analysis, presented in the third column, demonstrated a robust and positive influence of the DE on IEE. In conclusion, even when accounting for endogeneity, the consistent findings affirmed the strong positive impact of the DE on IEE. Additionally, considering the existence of autocorrelation and heteroskedasticity in the panel data, the two-stage least squares estimation results may be biased, so this paper adopted a more efficient systematic GMM method to estimate the basic mode. As shown in column 4 of Table 6, both AR1 and AR2 values were greater than 0.1, indicating that there was no autocorrelation in the randomly perturbed term, and it passed the Hansen test. The results again demonstrated that the DE had a significant positive coefficient at the 1% level.

Table 7. Results of endogeneity test.

	First Stage DE	Second Stage IEE	GMM
DE		2.486 *** (4.93)	0.210 *** (3.26)
Control variables	Yes	Yes	Yes
Instrumental variable	0.256 *** (7.43)		
F value	57.55		
AR1			0.001
AR2			0.857
Hansen test			0.947
N	410	410	369
R^2	0.659	0.243	

Note: The significance levels indicated by *** is 1%, with the T values in parentheses.

6. Conclusions and Discussion

6.1. Conclusions

This study conducted an analysis on panel data from 41 prefecture-level cities in the YRD region spanning from 2011 to 2020. The primary objective was to investigate the impacts of the DE on IEE. The analysis primarily focused on examining spatio-temporal correlation, as well as the direct and indirect effects between the DE and IEE. The study yielded several key findings.

Firstly, an inverted V-shaped fluctuating trend was observed in the temporal correlation intensity between the DE and IEE and SE. Conversely, there was a W-shaped fluctuation trend in the temporal correlation intensity between the DE and PTE. Regarding spatial correlation, the negative correlation between the DE and IEE was primarily clustered in Anhui and Jiangsu provinces, while the positive correlation was predominantly found in Zhejiang province. The southern regions of the delta exhibited stronger spatial correlation intensity between the DE and PTE, whereas the central and northern areas showed lower spatial correlations. Furthermore, the negative spatial correlation between the DE and SE was primarily concentrated in Anhui province, with scattered instances in Zhejiang and Jiangsu provinces. On the other hand, the cities with positive correlations were mainly concentrated in Jiangsu and Zhejiang provinces.

Secondly, the findings of this study confirmed that the DE had a significant positive and direct effect on IEE. It was established that the DE directly contributed to improving IEE in the examined period. Furthermore, the study revealed that the indirect effects of the DE on IEE were primarily driven by the enhancement of green technology innovation and the upgrading of industrial structure. These factors worked together to strengthen IEE and promote sustainability within the industrial sector.

Thirdly, this study found clear regional heterogeneity in how the growth of the DE impacted IEE in the YRD region. Specifically, while the non-core area effect was not found to be significant, the core area effect was considerable and favorable. The results demonstrated that the development of the YRD region followed a design principle that centered on the core city, utilizing a radiation effect to stimulate the growth and development of neighboring cities.

6.2. Discussion

One of the more significant findings to emerge from this study was that correlation over time between IEE and the DE followed an inverted V-shaped trend; one explanation for this result is that the development of the digital economy in the Yangtze River Delta region presents noticeable geographical differences, with large industrial enterprises mainly located in economically developed areas, while small- and medium-sized enterprises dominate in undeveloped regions [65]. In the initial stage, large industrial enterprises took the lead in the field of the digital economy, and these enterprises became the forerunners of the digital economy with their complete industrial base, scale advantage, and technological leadership. Over time, the digital economy has spread to less developed regions. However, small- and medium-sized enterprises have a relatively weak industrial base and face enormous technological challenges, which makes the transformation of industrial digitization an difficult test, thus showing an inverted V-shaped fluctuation trend. This discovery underscored the variations in industrial foundations and technological prowess among diverse regions. Thus, crafting distinct development strategies becomes imperative during the digital economy's advancement. Moreover, prominent industrial enterprises can fuel comprehensive advancement by engaging in technological exports and collaborative efforts.

Secondly, there was a W-shaped fluctuation trend in the temporal correlation intensity between the DE and PTE. The introduction and implementation of the digital economy involves phases of adaptation, adjustment, and investment, potentially causing variations in PTE. Over time, enterprises progressively acclimate to novel technology, leading to the gradual emergence of a return on investment. This phenomenon may, in turn, enhance PTE once more, thereby giving rise to a distinctive W-shaped fluctuation pattern. This finding suggests the need for a long-term perspective when assessing the impact of the digital economy, with companies looking not only at short-term fluctuations, but also at the sustained gains that the digital economy is likely to bring in the future. There is a necessity to balance investment with the expected returns, and to allocate resources wisely.

Thirdly, this study confirmed the direct impact of DE on IEE. This finding was in contrast to previous analyses of the impact on industrial development, which have been conducted only at the level of the Internet [38,39], and this paper broadened the perspective of research on industrial development. This finding substantiated that the convergence of the digital economy and industry not only fosters industrial economic growth, but also mitigates environmental burdens. Once again, it verified that the economy and the environment are not in opposition to each other, and that a double-win situation can be achieved through innovation and intelligent means [53]. Furthermore, in previous studies, the DE has been found to have a positive effect on both green technological innovation and industrial upgrading [52,54], and this outcome was reaffirmed in this paper. Moreover, this study integrated this result into the examination of IEE development. This research contributes to our understanding that DE has acted as a catalyst for innovation, providing crucial resources and capabilities for green technological innovation.

7. Suggestions and Limitations

7.1. Suggestions

This investigation into the impact of the DE on IEE in the YRD region holds immense significance in the context of fostering innovative economic development and ensuring sustainable growth. Consequently, pertinent recommendations have been proposed to fully harness the potential of the DE to drive industrial green growth.

Firstly, it is necessary to expedite the deep integration of information technology (IT) applications with industries across all stages, including production, distribution, circulation, and consumption. Cities in the YRD region should actively build safe, efficient, and flexible industrial Internet facilities and platforms to facilitate the seamless convergence of traditional industries with modern technologies such as big data and artificial intelligence. Moreover, in order to achieve the effective integration of the digital economy and industrial development, it is essential to establish relevant policies, provide financial support, strengthen intellectual property protection, establish collaborative mechanisms, enhance regulatory frameworks and standards, as well as optimize the business environment. In addition, the establishment of an enabling policy environment that supports sustainable industrial development is proposed. This includes the setting of clear targets and regulations for eco-efficiency, incentivizing the adoption of clean and renewable energy sources, and implementing effective waste management and pollution control measures.

Secondly, the formulation of a differentiated implementation path for the green development of digitally empowered industries is encouraged. Cities in the YRD core region should leverage their resource endowments, innovative elements, and technological advancements to drive industrial digitalization and establish a green and circular industrial system. On the other hand, cities in non-core regions should raise awareness of green development, adopt clean technologies and renewable energy sources to reduce carbon emissions and mitigate climate change impacts, and focus on green, low-carbon, and circular economic development, emphasizing the reuse, recycling, and resource recovery processes to minimize waste generation and promote sustainable resource management.

Thirdly, it is necessary to enhance regional cooperation and coordination within the YRD region and leverage the strengths and expertise of these two types of cities; collaborative initiatives can be developed to share best practices, facilitate knowledge transfer, and promote joint efforts towards achieving sustainable and green industrial development. Moreover, it is necessary to strengthen the collaborative efforts of governments, enterprises, and scientific research institutions to encourage cross-regional exchange of cutting-edge green innovation technologies, facilitating knowledge sharing and collaboration in the transition of industries towards sustainability and intelligence. By working together, these stakeholders could foster a supportive ecosystem for technological advancements in environmentally friendly practices.

7.2. Limitations

There were several limitations in this study that need to be acknowledged. Firstly, the assessment index for the digital economy may require further refinement considering the influence of data availability and the absence of a consensus on the accurate measurement of the DE. Secondly, although this study showed a favorable effect of the growth of the DE on IEE, it did not account for the potential impact of the DE in surrounding cities on the IEE of each city. This aspect could have been evaluated using a spatial econometric model to capture the spatial interdependence between cities within the YRD region. Thirdly, it is necessary to delve deeper to understand the heterogeneous influence of the DE on the IEE of cities with different sizes. Moreover, investigating the differential impacts of the DE on IEE in different periods could provide valuable insights into the temporal dynamics and trends. Addressing these limitations would enhance the robustness and comprehensiveness of future research in this area.

Author Contributions: Conceptualization, Z.L.; Methodology, B.S.; Formal analysis, W.Z. and B.S.; Writing—original draft, W.Z.; Writing—review and editing, Z.L. and S.S.; Visualization, Z.L.; Supervision, S.S. and B.S.; Funding acquisition, B.S. All authors have read and agreed to the published version of the manuscript.

Funding: The research was funded by the Postgraduate Research Innovation Program Project in Jiangsu Province (grant number KYCX23_3476), the Social Science Foundation of Jiangsu Province (grant number 20SHD009), and the Yangzhou University Qing Lan Project in 2021.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data available from the authors upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Fan, Y.P.; Fang, C.L.; Zhang, Q. Coupling coordinated development between social economy and ecological environment in Chinese provincial capital cities-assessment and policy implications. *J. Clean. Prod.* **2019**, *229*, 289–298. [CrossRef]
2. Zhao, X.; Shang, Y.; Song, M. Industrial structure distortion and urban ecological efficiency from the perspective of green entrepreneurial ecosystems. *Socio-Econ. Plan. Sci.* **2020**, *72*, 100757. [CrossRef]
3. Yu, Y.; Hou, J.; Jahanger, A.; Cao, X.; Balsalobre-Lorente, D.; Radulescu, M.; Jiang, T. Decomposition analysis of China's chemical sector energy-related CO_2 emissions: From an extended SDA approach perspective. *Energy Environ.* **2023**, 0958305X231151682. [CrossRef]
4. Yuan, X.; Liu, M.; Yuan, Q.; Fan, X.; Teng, Y.; Fu, J.; Ma, Q.; Wang, Q.; Zuo, J. Transitioning China to a circular economy through remanufacturing: A comprehensive review of the management institutions and policy system. *Resour. Conserv. Recycl.* **2020**, *161*, 104920. [CrossRef]
5. Liu, K.; Qiao, Y.R.; Zhou, Q. Analysis of China's industrial green development efficiency and driving factors: Research based on MGWR. *Int. J. Environ. Res. Public Health* **2021**, *18*, 3960. [CrossRef]
6. Zhou, L.L.; Li, W.Q. The impact of green M&A listed companies' size on the rural ecological environment—Digitalization as moderating effect. *Sustainability* **2023**, *15*, 6068.
7. Liu, J.; Liu, L.; Qian, Y. The effect of artificial intelligence on carbon intensity: Evidence from China's industrial sector. *Socio-Econ. Plan. Sci.* **2022**, *83*, 11002. [CrossRef]
8. Wang, J.; Zhu, J. Research on the Measurement of China's Digital Economy Development and the Characteristics. *J. Quant. Technol.* **2021**, *38*, 26–42.
9. Guo, B.N.; Wang, Y.; Zhang, H. Impact of the digital economy on high-quality urban economic development: Evidence from Chinese cities. *Econ. Model.* **2023**, *120*, 106194. [CrossRef]
10. Hao, X.; Li, Y.; Ren, S. The role of digitalization on green economic growth: Does industrial structure optimization and green innovation matter? *J. Environ. Manag.* **2023**, *325*, 116504. [CrossRef] [PubMed]
11. Li, R.; Rao, J.; Wan, L.Y. The digital economy, enterprise digital transformation, and enterprise innovation. *Manag. Decis. Econ.* **2022**, *43*, 2875–2886. [CrossRef]
12. Zhang, Q.; Yu, J. Input Digitization of Manufacturing Industry and Upgrading in GVC: Reexamination based on the Difference of Input Source. *J. Financ. Econ.* **2021**, *47*, 93–107.
13. Miao, Z.L. Digital economy value chain: Concept, model structure, and mechanism. *Appl. Econ.* **2021**, *53*, 4342–4357. [CrossRef]
14. Bukht, R.; Heeks, R. Defining, conceptualizing and measuring the digital economy. *Dev. Inform.* **2017**, *69*. [CrossRef]
15. Pan, W.R.; Xie, T.; Wang, Z.W. Digital economy: An innovation driver for total factor productivity. *J. Bus. Res.* **2022**, *139*, 303–311. [CrossRef]
16. Wang, W.; Jia, J.J.; Liu, Y.S. *Profound Changes Unseen in Centuries: An Overview of China*; Beijing Normal University Press (Group) Co., LTD: Beijing, China, 2022.
17. Moulton, B.R. *GDP and the Digital Economy: Keeping Up with the Changes. Understanding the Digital Economy Data*; MIT Press: Cambridge, MA, USA, 2000; pp. 35–48.
18. Li, K.; Kim, D.J.; Lang, K.R. How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electron. Commer. Res. Appl.* **2020**, *44*, 101004. [CrossRef]
19. Ren, S.; Hao, Y.; Xu, L.; Wu, H.; Ba, N. Digitalization and energy: How does internet development affect China's energy consumption? *Energy Econ.* **2021**, *98*, 105220. [CrossRef]
20. Zhao, T.; Zhang, Z.; Liang, S.K. Digital Economy, Entrepreneurship, and High-quality Economic Development: Empirical Evidence from Urban China. *Front. Econ. China* **2022**, *17*, 393–426.
21. Wang, L.H.; Shao, J. Digital economy, entrepreneurship and energy efficiency. *Energy* **2023**, *269*, 126801. [CrossRef]
22. Dong, F.; Hu, M.Y.; Gao, Y.J. How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci. Total Environ.* **2022**, *852*, 158401. [CrossRef]
23. Krotov, V. The Internet of Things and new business opportunities. *Bus. Horiz.* **2017**, *60*, 831–841. [CrossRef]
24. Zaki, M. Digital transformation: Harnessing digital technologies for the next generation of services. *J. Serv. Mark.* **2019**, *33*, 429–435. [CrossRef]
25. Muhammad, S.; Pan, Y.; Magazzino, C. The fourth industrial revolution and environmental efficiency: The role of fintech industry. *J. Clean. Prod.* **2022**, *381*, 135196. [CrossRef]
26. Liu, K.; Feng, Z.R.; Zhang, Q.H. Examining the role of digitalization and gig economy in achieving a low carbon society: An empirical study across nations. *Front. Environ. Sci.* **2023**, *11*, 1197708. [CrossRef]
27. Noussan, M.; Tagliapietra, S. The effect of digitalization in the energy consumption of passenger transport: An analysis of future scenarios for Europe. *J. Clean. Prod.* **2022**, *258*, 120926. [CrossRef]
28. Sui, D.Z.; Rejeski, D.W. Environmental impacts of the emerging digital economy: The E-for-environment E-commerce? *Environ. Manag.* **2002**, *29*, 155–163. [CrossRef] [PubMed]

29. Babu, B.R.; Parande, A.K.; Basha, C.A. Electrical and electronic waste: A global environmental problem. *Waste Manag. Res.* **2007**, *25*, 307–318.
30. Kuosmanen, T. Measurement and analysis of eco-efficiency: An economist's perspective. *J. Ind. Ecol.* **2005**, *9*, 15–18. [CrossRef]
31. Dahlstrom, K.; Ekins, P. Eco-efficiency trends in the UK steel and aluminum industries: Differences between resource efficiency and resource productivity. *J. Ind. Ecol.* **2005**, *9*, 171–188. [CrossRef]
32. Toma, P.; Miglietta, P.P.; Zurlini, G.; Valente, D.; Petrosillo, I.A. Non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries. *Ecol. Indic.* **2017**, *83*, 132–143. [CrossRef]
33. Lee, T.; Yeo, G.T.; Thai, V.V. Environmental efficiency analysis of port cities: Slacks-based measure data envelopment analysis approach. *Transp. Policy* **2014**, *33*, 82–88. [CrossRef]
34. Zhou, C.S.; Shi, C.Y.; Wang, S.J. Estimation of eco-efficiency and its influencing factors in Guangdong province based on Super-SBM and panel regression models. *Ecol. Indic.* **2017**, *86*, 67–80. [CrossRef]
35. Yu, Y.T.; Huang, J.H.; Zhang, N. Industrial eco-efficiency, regional disparity, and spatial convergence of China's regions. *J. Clean. Prod.* **2018**, *204*, 872–887. [CrossRef]
36. Ren, Y.F.; Fang, C.L.; Li, G.D. Spatiotemporal characteristics and influential factors of eco-efficiency in Chinese prefecture-level cities: A spatial panel econometric analysis. *J. Clean. Prod.* **2020**, *260*, 120787. [CrossRef]
37. Liu, Q.; Wang, S.; Li, B.; Zhang, W. Dynamics, differences, influencing factors of eco-efficiency in China: A spatiotemporal perspective analysis. *J. Environ. Manag.* **2020**, *264*, 110442. [CrossRef]
38. Ranta, V.; Aarikka-Stenroos, L.; Visnen, J.M. Digital technologies catalyzing business model innovation for circular economy—Multiple case study. *Resour. Conserv. Recycl.* **2021**, *164*, 105155. [CrossRef]
39. Zhang, W.; Zhao, S.Q.; Wan, X.Y.; Yao, Y. Study on the effect of digital economy on high-quality economic development in China. *PLoS ONE* **2021**, *16*, e0257365. [CrossRef] [PubMed]
40. Luo, K.; Liu, Y.B.; Chen, P.F. Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. *Energy Econ.* **2022**, *112*, 106127. [CrossRef]
41. Wang, L.; Wu, Y.H.; Huang, Z.Y. How big data drives green economic development: Evidence from China. *Front. Environ. Sci.* **2022**, *10*, 1055162. [CrossRef]
42. Che, S.; Wang, J. Digital economy development and haze pollution: Evidence from China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 73210–73226. [CrossRef] [PubMed]
43. Qi, G.; Wang, Z.; Wang, Z. Has industrial upgrading improved air pollution? —Evidence from China's digital economy. *Sustainability* **2022**, *14*, 8967. [CrossRef]
44. Wang, L.; Chen, L. Resource dependence and air pollution in China: Do the digital economy, income inequality, and industrial upgrading matter? *Environ. Dev. Sustain.* **2022**, 1–14. [CrossRef]
45. Lei, X.Y.; Ma, Y.F.; Ke, J.K. The non-linear impact of the digital economy on carbon emissions based on a mediated effects model. *Sustainability* **2023**, *15*, 7438. [CrossRef]
46. Li, Z.G.; Wang, J. The dynamic impact of digital economy on carbon emission reduction: Evidence city-level empirical data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
47. Zhang, W.; Zhou, H.; Chen, J. An empirical analysis of the impact of digital economy on manufacturing green and low-carbon transformation under the dual-carbon background in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 13192. [CrossRef]
48. Wu, L.; Wan, X.W.; Jahanger, A. Does the digital economy reduce air pollution in China? A perspective from industrial agglomeration. *Energy Rep.* **2023**, *9*, 3625–3641. [CrossRef]
49. Wan, Q.; Shi, D. Smarter and cleaner: The digital economy and environmental pollution. *China World Econ.* **2022**, *30*, 59–85. [CrossRef]
50. Dong, R.; Zhou, X. Analysis of the nonlinear and spatial spillover effects of the digital economy on carbon emissions in the Yellow River Basin. *Sustainability* **2023**, *15*, 5253. [CrossRef]
51. Shen, G.B.; Yuan, Z.Y. The Effect of Enterprise Internetization on the Innovation and Export of Chinese enterprises. *Econ. Res. J.* **2020**, *55*, 33–48.
52. Wei, L.I.; Hou, Y.Q. Research on the Impact of China's Digital Economic on Urban Green Development. *J. Quant. Technol.* **2022**, *39*, 60–79.
53. Luo, J. The Spatial Effect of Urban Digital Economy on the Green Development of Manufacturing Industry. *Econ. Geogr.* **2022**, *42*, 13–22.
54. Chang, X. Digital Economy, Industrial Structure Upgrade and Common Prosperity. *J. Tech. Econ. Manag.* **2022**, *12*, 10–16.
55. Pil, S.H.; Duk, H.L. Evolution of the linkage structure of ICT industry and its role in the economic system: The case of Korea. *Inf. Technol. Dev.* **2019**, *25*, 424–454.
56. Guo, M.C. Research on the Relationship between ICT Industry and the Optimization and Upgrading of Industrial Structure-Analysis based on gray correlation entropy modeling. *Inq. Into Econ. Issues* **2019**, *4*, 131–140.
57. Zuo, P.F.; Jiang, Q.P. Internet Development, Urbanization and the Upgrading of China's Industrial Structure. *J. Quant. Technol.* **2020**, *37*, 71–91.
58. Sun, J.; Dang, Y.G.; Zhu, X.Y. A grey spatiotemporal incidence model with application to factors causing air pollution. *Sci. Total Environ.* **2021**, *759*, 143576. [CrossRef] [PubMed]

59. Li, Z.J.; Zheng, X.; Sun, D.Q. The influencing effects of industrial eco-efficiency on carbon emissions in the Yangtze River Delta. *Energies* **2021**, *14*, 8169. [CrossRef]
60. Li, Z.J.; Zhang, W.J.; Sarwar, S. The spatio-temporal interactive effects between ecological urbanization and industrial ecologization in the Yangtze River Delta region. *Sustain. Dev.* **2023**, 1–18. [CrossRef]
61. Zha, J.P.; Dai, J.Q.; Xu, H. Assessing efficiency and determinants of tourist attractions based on a two-subprocess perspective: A case of Chengdu, southwestern China. *J. Destin. Mark. Manag.* **2021**, *19*, 100542.
62. Luigi, A.; Mohsen, B.; Concetto, P.V. Knowledge spillovers and technical efficiency for cleaner production: An economic analysis from agriculture innovation. *J. Clean. Prod.* **2021**, *320*, 128830.
63. Luo, R.; Zhou, N.X. Dynamic evolution, spatial differences, and driving factors of China's provincial digital economy. *Sustainability* **2022**, *14*, 9376. [CrossRef]
64. Zhao, D.F.; Li, C.B.; Wang, Q. Comprehensive evaluation of national electric power development based on cloud model and entropy method and TOPSIS: A case study in 11 countries. *J. Clean. Prod.* **2020**, *277*, 123190. [CrossRef]
65. Ye, C.; Zhu, J.; Li, S.; Yang, S. Assessment and analysis of regional economic collaborative development within an urban agglomeration: Yangtze River Delta as a case study. *Habitat Int.* **2019**, *83*, 20–29. [CrossRef]