Heliyon 10 (2024) e25686

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Does digital technology promote carbon emission reduction in the service industry: Economic logic and empirical evidence from China

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ARTICLE INFO

Keywords:
Digital technology
Carbon emission reduction
Service industry

ABSTRACT

Digital technology enables the service industry to develop rapidly, which also brings about the increase of carbon emissions in the service industry (CESI). How to better integrate the service industry into China's carbon emission reduction model has become an important content that the Chinese government needs to pay attention to. This paper uses the industry-level panel data of the service in 30 provinces of China from 2008 to 2019 to examine the relationship between the degree of digital technology and CESI through theoretical and empirical methods. The results reveal that there is an inverted U-shaped relationship between digital technology and CESI, and the effect of digital technology on curbing CESI is limited. Furthermore, the pilot policy of carbon market reduces CESI by 173.17 Mt and CESI per 10,000 people by 0.0065 Mt. Resource differences, regional differences and industrial structure differences bring about heterogeneous impacts. The Chinese government in particular, and the government established by the carbon emission reduction model should pay attention to promoting the digital transformation of the service industry to achieve the carbon emission reduction target, but the digital transformation of the service industry should be carried out in a hierarchical and orderly manner under the coordination of the government.

1. Introduction

Global warming is a serious threat to people's survival [1,2], and human activities have been the main source of greenhouse gases such as carbon dioxide since the mid-20th century. However, the main source of these greenhouse gases is the consumption and use of fossil energy. Especially since the COVID-19 pandemic, fluctuations in energy prices caused by macroeconomic uncertainties have caused human concerns about energy consumption [3]. Further, human beings push the concept of sustainable development to a higher level [4]. A typical example is Canada's integration of the concept of sustainable development into financial development and technological progress [5]. Of course, there are many examples of sustainable development, including countries such as India, Pakistan and Lebanon [6–8], as well as regions such as the Middle East, North America and Latin America [9,10]. The advent of digital technology has further accelerated the growth rate of carbon emissions. Environmental issues and sustainable development are emphasized again and become a focal issue of concern around the world. From 2020 to 2022, the world's carbon emissions continue to

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https://doi.org/10.1016/j.heliyon.2024.e25686
Received 7 November 2023; Received in revised form 25 January 2024; Accepted 31 January 2024
Available online 7 February 2024
2405-8440/

grow from 33.46 Gt to 36.11 Gt.[1] According to Emissions Database for Global Atmospheric Research (EDGAR), China's carbon emission ranks first in the world and far exceeds that of the second place (USA) which means that the study of China's carbon emission is of great significance to the world's carbon emission control. Moreover, with the promotion of digital technology, the increasing contribution of China's service industry to the economy increases the difficulty of the world's carbon emission governance. Does the development of digital technology reduce industrial carbon emissions while promoting economic development? How will the development of digital technology affect the pattern of carbon emission governance in China and even the world? Therefore, studying the impact of digital technology on the carbon emissions is of practical significance.

The service industry has grown rapidly with China's rise. By 2021, the service industry contributes 54.9%[2] to China's GDP, which is of great significance to China's economic development and resident employment. Since China put forward the carbon market construction plan in 2011, the carbon emission reduction plan of agriculture and industry has been rapidly put on the agenda. The carbon emission reduction plan of agriculture and industry has achieved certain results [11], while the carbon emission reduction plan of service industry lags behind that of agriculture and industry significantly. On the one hand, CESI are lower than those of the secondary industry, and the difficulty of governance is relatively low. From 2011 to 2018, the carbon emissions of secondary industry accounted for 70%,[3] larger than the carbon emissions of the primary industry and the tertiary industry combined; On the other hand, the growth rate of CESI is obvious, and the task of governance is imminent. CESI show the characteristics of relatively low total amount and relatively fast growth, which makes it of great significance to further discuss and study the carbon emission reduction of the service industry.

The digital technology and digitalization and informatization reform of the service industry has risen rapidly driven by China's innovation-driven development strategy. In this context, digital economy and digital technology drive each other and have a profound impact on China's service industry. The development of digital economy has a certain impact on the structural adjustment of the industry, technological innovation and the efficiency of the carbon emission trading market.

At this special stage of development, exploring the impact of the development of digital economy and digital technology on CESI is of great practical significance. Based on this reality, this paper focuses on the impact of digital technologies on CESI. Specifically, this paper derives and verifies the relationship between digital technology and CESI. Through further research, this paper examines the impact of digital technology on CESI and the role of carbon market policies. This paper explores the effect and path of the impact of digital technology on CESI, which provides certain enlightenment for the governance of CESI.

The marginal contributions of this paper are as follows: (1) In terms of service industry, this paper uses mathematical model to analyze the relationship between the development of digital technology and CESI, which makes up for the deficiency of the academic research on CESI. (2) In terms of theory, this paper uses digital technology as a proxy variable to study the environmental problems of the service industry, which further expands the study of Environmental Kuznets Curve (EKC). (3) In terms of policy, this paper puts forward relevant measures for carbon emission reduction in the service industry, which has implications for policy making in China and other countries exploring carbon emission reduction models.

The subsequent sections of this paper are arranged as follows: Section 2 is literature review; Section 3 is theoretical analysis and research hypothesis; Section 4 is variable selection and model construction; Section 5 is research results and analysis; Section 6 is discussion. Section 7 is conclusion and recommendation. This paper expands the relevant literature on digital technology and service industry, and fills the gap in the research field of digital technology development and carbon emission reduction in service industry.

2. Literature review

With the emergence of environmental problems represented by carbon emissions, existing researches begin to pay attention to the study of topics such as carbon emission reduction. Topics about the relationship between structural change [12], trade openness [13] and carbon emissions keep emerging. Digital technology rapidly enables agriculture, manufacturing and service industries, creating opportunities for industrial development and greatly promoting the development of digital economy. Furthermore, people begin to think about the feasibility of using digital technology to enable carbon emission reduction. Digital technology has the characteristics of low cost and high precision, and the use of this technology to track carbon emissions creates the conditions for carbon reduction in all industries. Therefore, this paper reviews the existing literature from the following perspectives. The logical framework is shown in Fig. 1.

2.1. Manufacturing industry and carbon emissions

The research on carbon emissions first comes from the manufacturing industry, while the research on the service industry is relatively scarce. The large carbon emissions of the manufacturing industry mean that the researches on the manufacturing industry first enter the vision of scholars. Specifically, Ang (2009) analyzes the influencing factors of carbon emissions based on the significance of China's carbon emissions for world environmental protection [14]. The research believes that scientific research intensity and technology transfer were effective for carbon emission reduction. Pindyck (2013) argues that the comprehensive assessment model (IAMs) does not analyze the most important factors affecting the social cost of carbon (SCC) [15]. Bijgaart et al. (2013) break through

[1] Data from Carbon Monitor, URL: https://www.carbonmonitor.org.cn/.
[2] Data from the official website of the National Statistical Office, URL: https://data.stats.gov.cn/easyquery.htm?cn=C01.
[3] Data from World Bank World Development Indicators (WDI), International Energy Agency (IEA), National Bureau of Statistics.

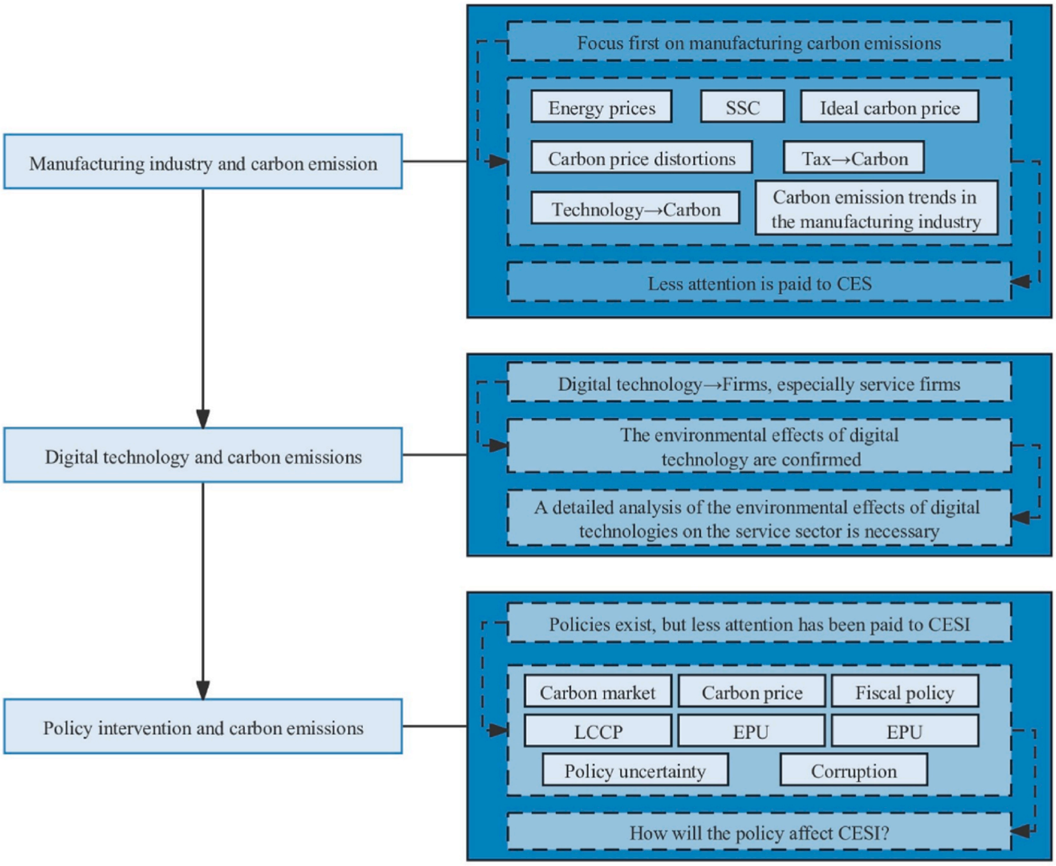

Fig. 1. The logical framework of the literature review.

the limitations of IAMs and establish a closed-form formula for calculating SCC [16]. Vaninsky uses the generalized Divisia index method to consider carbon emissions [17]. Based on this method, Shao et al. (2013) analyze the evolutionary trend of carbon emissions in the manufacturing industry [18]. Existing studies also use DEA, EIO-LCA model, C-CGEM and other models to calculate carbon emission efficiency [19–21]. Gugler et al. (2021) further prove the role of carbon tax in carbon emission reduction and analyzes the efficiency of carbon tax policy and subsidy policy by using the actual data of European countries [22]. The results confirm the important role of carbon tax in electricity and other industries. Some researches study the carbon emissions of manufacturing industry from the perspectives of energy price, ideal carbon price and carbon emission price distortion [23–25]. Yang et al. (2022) analyze the distorting effect of shadow carbon price based on manufacturing industry, the result shows that the distorting effect of the shadow price of carbon emissions shows an inverted U-shaped change [25]. Li et al. (2022) explore the situation of China's power market, the research reveals that the deadweight loss rate in the electricity market is lower in the carbon market pilot regions [24]. Yang et al. (2023) find that the price distortion coefficient of energy relative to capital in industrial production is 0.78 [23]. Additionally, some studies put forward views on how to achieve the path and effect of carbon emission reduction in the manufacturing industry, and examined the optimal path of carbon emission reduction across stages and the social welfare effect of carbon emission reduction [26, 27]. It is worth noting that the existing researches pay relatively little attention to the carbon emissions of the service industry. Especially for China which is at the beginning of the establishment of the carbon emission reduction model, there is even a lack of research on how to conduct carbon emission reduction in the service industry.

2.2. Digital technology and carbon emissions

The development of digital technology is of great significance to modern society, and the channels through which digital economy affects enterprises are very consistent with the service industry. However, few studies make a detailed analysis of the impact of digital technology on the service industry. Digital technology can play an important role in the development of modern enterprises through channels such as labor substitution effect, industrial chain, scale effect and wage distortion [28–30]. Specifically, Acemoglu and Restrepo (2019) establish a task-based model, and a large number of studies on digital technology, industrial robots and labor are carried out under this framework, continuously expanding the economic effect of digital technology [31]. Since Selton and Song (1995) introduce the variable of environmental pollution into the neoclassical growth model and analyze the relationship between economic growth and environmental pollution, the proxy variable of economic growth has also been changing [32]. With the development of digital technology, the research focus gradually changes to the economic effect and environmental effect of digital technology. In some researches on the calculation of carbon emission efficiency, the role of digital technology is revealed through the method of factor decomposition, which confirms the environmental effect of digital technology. Therefore, digital technology is introduced into the model and analyzed in detail as a proxy variable for economic growth [33]. From the perspective of income, Du et al. (2019) use the panel data of 71 economies from 1996 to 2012 to analyze the impact of digital technology progress on carbon emissions of different countries, and reveal that the effect of digital technology progress on carbon emission reduction of low-income countries is lower [34]. Jiang et al. (2022) analyze the impact of the introduction of digital technology represented by robots on the carbon emission reduction of the manufacturing industry, and believe that every 1% increase in the impact of robots reduce the carbon emission of the manufacturing industry by 0.96%. Moreover, it is believed that the impact of robots for industries with high energy consumption is more obvious [35]. Wang et al. (2023) use natural resource rent and anti-corruption regulation as threshold variables to analyze the relationship between digital economy and carbon emissions, and believe that there is an inverted U-shaped relationship between digital economy and carbon emissions [36]. Yang et al. (2023) establish an endogenous growth model and clearly point out that digital technology has a carbon emission reduction effect [37]. Research reveals that the environmental effect of digital technology includes technological progress channel, energy utilization efficiency channel and technological diversity channel. Additionally, Goldfarb and Tucker (2019) clearly point out that digital technology dominates the development of modern industries, especially the development of the service industry [38]. Moreover, the impact of digital technology on modern economic activities is proposed, including search costs, replication costs, transportation costs, tracking costs, and verification costs. The service industry is characterized by a large number of employees and extensive contact with consumers, which makes these influence channels consistent with the service industry. However, the existing research rarely analyzes the impact of digital technology on the service industry.

2.3. Policy intervention and carbon emissions

Although there are a large number of studies on carbon emission reduction policies in the literature, few studies focus on the impact of carbon emission reduction policies on the service industry. Carbon reduction models in many countries combine government functions with market mechanisms. For example, Wu et al. (2021) find that China uses the synergy of administrative intervention and market mechanism to promote national carbon emission reduction [39]. Common policy interventions include decentralizing fiscal power, improving carbon emission efficiency, carbon pricing, carbon tax and promoting enterprise technological innovation [40–43]. Zhang et al. (2011) analyze the environmental impact of fiscal decentralization and the results shows that the impact of fiscal decentralization on the increase of carbon emissions is mainly through the secondary and tertiary industries [41]. Acemoglu et al. (2012) point out that the impact of fiscal decentralization on the increase of carbon emissions is mainly through the secondary and tertiary industries [43]. Aatola et al. (2013) analyze the impact of carbon price on carbon emission reduction based on the European electricity market and find that it has a positive impact, but the impact was uneven [44]. Barrage (2019) further studies carbon tax, arguing that carbon tax is affected by distorting monetary policy [45]. Therefore, the optimal carbon tax is analyzed in a dynamic general equilibrium climate-economy model with distortionary fiscal policy. The research finds that the optimal carbon tax schedule is 8% lower when distortionary taxes are present. Nordhaus (2019) analyses the limited success of international environmental treaties [42]. Jin et al. (2022) believe that carbon price, emission efficiency improvement and asset structure decarbonization are important mechanisms to solve the problem of carbon emissions，and the results reveal that the combined effect of the three mechanisms can not only help achieve the net zero carbon emission target, but also promote endogenous economic growth [40]. It needs to be emphasized that the difference brought by carbon tax is combined with the market mechanism to have an impact on enterprise technological innovation [46]. Policy uncertainty and government corruption also lead to differences in corporate carbon emissions [47–49]. Under the leadership of the government, the establishment of carbon market system is crucial for the governance of carbon emissions. Yu and Zhang (2021) study the relationship between low-carbon city pilot policy (LCCP) and carbon emission efficiency, and analyze it under the framework of difference-in-difference (DID) and spatial DID (SDID) [50]. It is found that LCCP improves carbon emission efficiency by 1.7%. Dechezleprêtre et al. (2023) reveal the impact of the European Union Emissions Trading System (EU ETS) on carbon emissions and economic performance [51]. The results show that ETS reduces corporate carbon emissions by 10% and has no significant impact on corporate profits and employment. Since China's carbon market is still in its infancy, the targets of carbon market, carbon price and other policies are mainly manufacturing enterprises with high carbon emissions, while there are few special policies for service industries. Therefore, the impact of policies such as the pilot of the carbon market on the carbon emissions of the service industry has been less concerned by the existing research.

In summary, existing studies are mainly missing in three aspects after reviewing the above literature. First, the existing research mainly takes the manufacturing industry as the sample and uses the data of the manufacturing industry to study the carbon emission issue. Second, the existing research pays little attention to the close relationship between digital technology and the development of the service industry, especially the environmental effect of digital technology on the service industry. Thirdly, the existing research fails to take China's service industry into consideration in the carbon market and other policy tools due to the immaturity of China's carbon emission reduction model and other reasons. Therefore, this paper makes up for the above research gaps. Using the data of China's service industry development as a sample, this paper examines the relationship between the development of digital technology and CESI, and examines the impact of the carbon market pilot policy on CESI. The conclusion of this study has important implications for China and other countries, especially emerging countries.

3. Theoretical analysis and research hypothesis

In the wave of digital economy and informatization reform, artificial intelligence, blockchain technology and other digital technologies have a profound impact on the digital transformation of service enterprises. Service enterprises in the process of digital transformation have an impact on the company's carbon emissions, which promote or inhibit the effect of China's carbon emission policy.

In this paper, the production function of service firms is set as $Q = AN^{\alpha}K^{\beta}$, which is a Cobb-Douglas production function [52]. This paper has output of service industry firms Q as a function of the comprehensive technology level of service industry firms, the labor of service industry firms and the capital of the service industry firm, A, N and K. A、α、β satisfy $A > 0, 0 < \alpha < 1, 0 < \beta < 1$, respectively [52]. The additional CO_2 emission T is represented by output of service industry firms Q and the pollution factor z. The functional relationship is denoted as $T = Qz$ [53]. Let e to denote the carbon emission allowance set by the government where $e > 0$, and t to denote the carbon emission of service enterprises where $t = T - e$. The advancement of digital technology drives the development of the digital economy of the firms [53]. So, let L to denote the level of the digital economy of the firms and F to denote the advancement of digital technology. Then the relationship between them is $L = \theta_L F$, where $\theta_L > 0$. θ_L represents the digital propensity of the enterprise. Furthermore, this paper believes that the level of the digital economy of the firms L has a positive impact on the comprehensive technology level of service industry firms A. Therefore, this paper let A_0 to denote the comprehensive technology level of service enterprises before the reform of informatization, and $\theta_A > 0$ to denote that the marginal impact of the enterprise digitization level on the enterprise's comprehensive technology level is positive. Finally, $A(L) = A_0 + \theta_A L$ [54] is obtained.

In the process of the rise of digital economy, it leads to the increase of enterprise output, which has a positive impact on carbon emissions [55–59]. This paper let $z = z_0 + \theta_z L$, where z_0 is the carbon emission pollution factor existing when the enterprise has not carried out digital transformation, and $\theta_z > 0$ means that the carbon emission pollution factor of the enterprise has a positive impact with the improvement of the digital economy of the enterprise.

In addition, this paper assumes that service industry firms are in a perfectly competitive market, where the price of service industry products p is exogenous. Let C_0 to denote the fixed cost and b to denote the unit cost change of the product, where $p - b > 0$. The cost of carbon emission treatment is related to the additional CO_2 emission T. When the additional CO_2 emission is higher, the firm needs to spend more [39]. Therefore, the cost of carbon emission treatment is $C_T = \theta_c T$ [60], where $\theta_c > 0$. In summary, the profit function and constraints of the service industry enterprises are obtained:

$$\pi = (p - b)Q - C_0 - C_T \tag{1}$$

$$\text{s.t} \begin{cases} T = Qz \\ A(L) = A_0 + \theta_A L \\ z = z_0 + \theta_z L \\ Q = AN^{\alpha}K^{\beta} \\ C_T = \theta_c T \\ L = \theta_L F \\ 0 < \alpha, \beta < 1, \theta_A, \theta_c, \theta_L, \theta_z > 0, p > b \end{cases}$$

Service firms achieve the optimal level of digitization through digital reforms, which in turn maximizes profits. Therefore, we obtain Equation (2) taking the partial derivative of Equation (1) with respect to L:

$$\frac{\partial \pi}{\partial L} = (p - b - \theta_c z)\theta_A N^{\alpha} K^{\beta} - \theta_c \theta_z Q \tag{2}$$

By setting Equation (2) as 0, the optimal digitization level of service enterprises is obtained when they are at the best profit. By further organizing it, the corresponding enterprise output at the optimal digitalization level of the enterprise can be obtained as Equation (3):

$$Q^* = \frac{(p - b - \theta_c z)\theta_A N^{\alpha} K^{\beta}}{\theta_c \theta_z} \tag{3}$$

Multiplying both sides of Equation (3) by the pollution factor z, the additional carbon emissions corresponding to the service enterprises is obtained when they choose the optimal digitalization level, as shown in Equation (4):

$$T^* = \frac{z(p - b - \theta_c z)\theta_A N^{\alpha} K^{\beta}}{\theta_c \theta_z} \tag{4}$$

From Equation (4), it is easy to see that z is the function of the advancement of digital technology F, and T^* is a function of F. Therefore, the relationship between additional carbon emissions T^* and F can be obtained by taking the first and second partial derivatives of T^* with respect to F, respectively. The results are shown in Equations (5) and (6):

$$F^* = \frac{p - b}{2\theta_c \theta_L \theta_z} - \frac{z_0}{\theta_L \theta_z} \tag{5}$$

$$\frac{d^2 T}{dF^2} = -2\theta_A \theta_z {\theta_L}^2 N^{\alpha} K^{\beta} \tag{6}$$

It is not difficult to find from Equation (6) that $\frac{d^2T}{dF^2} < 0$. Therefore, F^* is the maximum point of the additional carbon emission T. Thus. The trend of carbon emissions is increasing first and then decreasing during the improvement of digital technology development, showing an inversed U-shaped nonlinear relationship.

The above analysis is an extension of EKC hypothesis, which is an important topic discussed in the study of economic growth and environmental pollution. And it is generally believed that the relationship between economic growth and environmental pollution mainly shows an “inverted U-shape” relationship. The relationship between technological innovation and CESI studied in this paper is indeed based on this theoretical hypothesis. The research framework is shown in Fig. 2.

First, digital technology can have a promoting effect on carbon emissions in the service industry. Within a certain period of digital economy development, especially when the level of digital economy development is low, the promoting effect of digital technology on carbon emissions is more obvious [58]. Specifically, on the one hand, the development of digital technology can promote advanced industrialization and digital technology drives the rapid expansion of the service industry in the short run [61], which promotes the increase of CESI. On the other hand, the development of digital technology requires the input of relevant infrastructure equipment [62]. In the early stage of digital technology development, the service industry needs to prepare relevant supporting equipment for digital transformation. Due to the relationship between the service industry and digital technology, other industries, digital transformation not only requires hardware equipment provided by the manufacturing industry, but also has an extremely huge demand for software industry provided by the Internet, software and other service industries [63,64]. Therefore, the service industries using digital equipment generate more carbon emissions due to the increase in inputs, thus increasing the pressure to reduce carbon emissions in the early stage.

Second, the development of digital technology has a restrict effect on service industry from internal and external source. It should be noted that the constraints on enterprises are small in the early stage, and enterprises need sufficient support at this stage, while too many constraints can easily lead to the early death of enterprises [65–67]. Therefore, the constraint effect is more significant when digital technology develops to a certain scale. In terms of the internal constraint, the development of digital technology expands the enterprises, which significantly reduce the overall carbon emissions within the supply chain [68]. Digital technology enables the service industry to change its business model and monitor carbon emissions digitally, which also promotes carbon reduction in the service industry. In terms of the external constraint, the power of the government, the market and consumers are also making service enterprises develop in the direction of low carbon. The government guides service enterprises to develop in a more environmentally friendly and green direction in the process of integration with digital technology through laws, economic policies and other means [40–42]. For example, under the framework of “Environment, Society and Governance (ESG)”, the government requires service industry enterprises to develop with the goal of energy conservation and emission reduction [69]. The market mechanism represented by the carbon market takes the service industry into account by means of carbon pricing and further constrain the carbon emissions of service enterprises [50]. As for consumers, the change of the meaning of environmental view exert pressure on service enterprises. The meaning of environment for consumers has gradually changed from a cheap product to a luxury product, and the change of environmental view reflects that people’s attention to the environment is further strengthened in the process of development [59]. Consumers shift their pressure on the environment to service enterprises to promote their carbon emission reduction. Summarizing the above discussion, this paper puts forward the following hypotheses:

Hypothesis. In the process of the development of digital economy, there is an "inversed U shaped" relationship between carbon emissions from service industries and the development of digital technology.

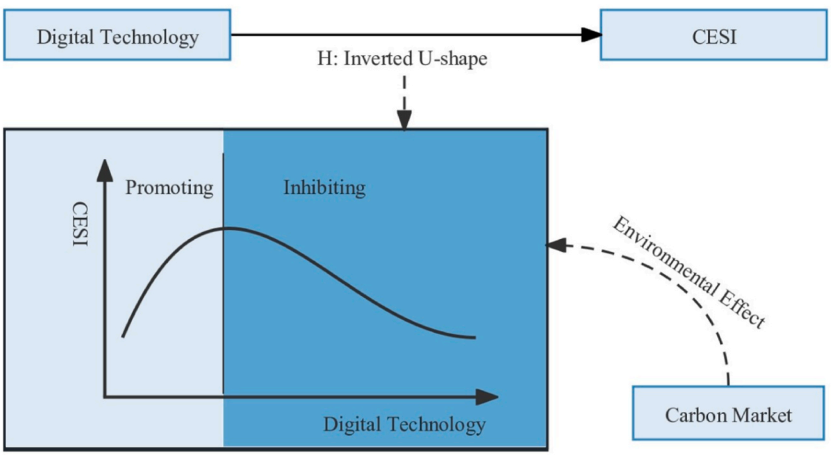

Fig. 2. Framework of digital technology and CESI.

4. Variable selection and model design

4.1. Model design

In order to examine the relationship between digital technology and CESI, this paper sets the model with reference to the relevant literature [70] and the basic form of the EKC [49]. The following model is set up:

$$ln\ co_{2itf} = \beta_0 + \beta_1 EIE_{itf} + \beta_2 EIE_{itf}^2 + \beta_3 control_{itf} + \gamma_i + \delta_t + \eta_f + \varepsilon_{itf} \tag{7}$$

In this model, subscripts *i*, *t*, and *f* denote industry, year, and province, respectively. $ln\ co_{2itf}$ is the dependent variable, denoting the carbon emission intensity; EIE_{itf} represents the degree of digital technology. EIE_{itf}^2 is the quadratic term of EIE_{itf}. $control_{itf}$ represents the control variable, including number of people working, urbanization rate, etc; γ_i denotes industry fixed effects; δ_t denotes time fixed effects, controlling for time-varying factors affecting carbon emissions in all industries; η_f is the province fixed effect; ε_{itf} denotes the random perturbation term. When $\beta_1 > 0$ and $\beta_2 < 0$, there is an inverted U-shaped relationship between CESI and the degree of digital technology.

By adding fixed effects and control variables, this paper can test the relationship between the degree of digital technology and CESI. This paper can further analyze the shape of the inverted U-shaped curve through the threshold effect model, which is of great significance for deepening the understanding of the relationship between the degree of digital technology and CESI. Finally, this paper uses the difference-in-difference-in-difference (DDD) method and heterogeneity analysis method to analyze the carbon market, resource endowment difference, regional difference and industrial structure difference in detail. These analyses have important implications for us to deeply understand the relationship between the degree of digital technology and CESI. It has an important enlightenment effect on the development of digital technology and the solution of carbon emission problems. The detailed methodological logic and analysis objects are shown in Fig. 3.

4.2. Variable selection

This paper selects carbon emissions data of various industries in the service industry at the level of 30 provinces (municipalities directly under the central government) in China from 2008 to 2019 for empirical analysis. The data are mainly from the China Carbon Accounting Databases (CEADs) [71–74], the China Stock Market & Accounting Research (CSMAR), the Wind database (Wind) and the National Bureau of Statistics of China. Given the availability and completeness of the sample data in the CEADs, this paper selects the carbon emissions data of the services industry starting from 2008 and the most recent data from 2019. Excluding the residual data, 4860 data were finally obtained.

The explanatory variable is the carbon emissions intensity, which is measured by the carbon emissions of a service industry in a given province. As the value of the explanatory variable is too large, the logarithmic form is used for carbon emissions. Due to the underdevelopment of a particular service industry in some provinces, the carbon emissions are small and the CEADs database automatically represents them with a value of 0 during processing. Therefore, the explanatory variable is treated as follows, where *i* denotes the service industry sector, *t* denotes the statistical time and *f* denotes the province:

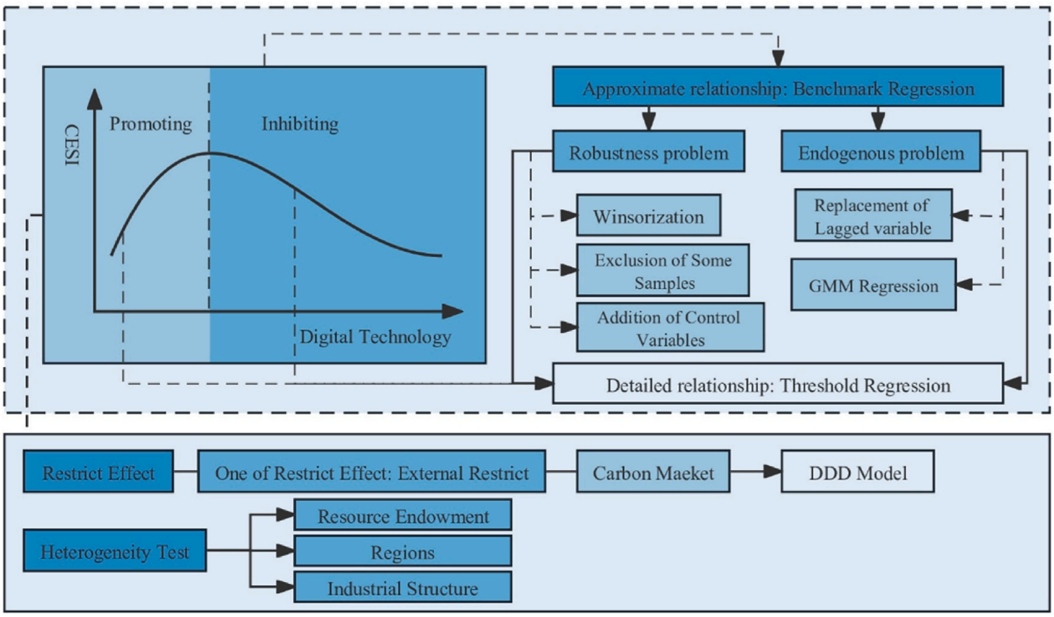

Fig. 3. The logic of methodology and the object of analysis.

$$ln\ co_2 = \ln\left(CO_{2itf} + 1\right), i = 1, 2, \ldots, 14; t = 2008, 2009, \ldots, 2019\ ; f = 1, 2, \ldots, 30 \quad (8)$$

The core explanatory variable is the degree of digital technology, and this paper utilizes the keywords “artificial intelligence”, “blockchain”, “big data”, “cloud computing”, “digital technology” and other keywords closely related to digital technology and digital economy in the annual reports of listed companies to measure the degree of regional digital technology according to Wu et al. (2021) and Zhao et al. (2021) [75,76]. This paper processes the data in CSMAR to portray it by utilizing the frequency of keywords in the annual reports of listed companies.

Since the carbon emissions of the service industry in each region are closely related to the level of economic development, the level of development of the industry and other factors, it is necessary to use control variables to restrict the regression equation in order to ensure the comparability of the regression. This paper selects control variables by referring to relevant literature. The control variables are the number of people working [77], urbanization rate [78], the development of service industry [78,79], the population density [80], education level [81,80], the fiscal decentralization [82,78], the level of economic development [78,77], the Internet penetration [81] and the degree of population growth [80], which are respectively used to control the level of development of each province, each industry, the potential for development and so on. Among them, the ratio of local government revenue (expenditure) to central government revenue (expenditure) is used to measure fiscal decentralization (*FPD*) [82]. The calculation methods of other explanatory variables, core explanatory variables and control variables are detailed in Table 1, and the results of descriptive statistics are detailed in Table 2.

5. Research results and analysis

5.1. Benchmark model results

Table 3 presents the results of the benchmark models, all of which control for time fixed effects, province fixed effects, and industry fixed effects. M_1 in Table 3 shows the analysis results with only the first power term of the core explanatory variable (*EIE*) added. M_2 introduces the variable EIE^2 based on the regression of M_1. The regression results of M_3, M_4 and M_5 introduce variables in turn according to the order of demographic characteristics, industrial characteristics and provincial characteristics. As can be seen from Table 3, there is a significant positive correlation between carbon emissions and *IE* $(EIE, M_2, r = 1.995, p < 0.01)$, and a significant negative correlation between carbon emissions and EIE^2 $(EIE^2, M_2, r = -0.223, p < 0.01)$ after introducing only *EIE* and EIE^2, which is consistent with the inverted U-shaped relationship. When all the control variables are introduced, the coefficient of *EIE* are still significantly positive at the 1% level $(EIE, M_5, r = 1.449, p < 0.01)$. The significance level of the coefficients of the core explanatory variables EIE^2 decreases slightly, but they are still significantly negative at the 5% level. $(EIE^2, M_5, r = -0.138, p < 0.05)$. This result satisfies the hypothesis that the coefficient of the first power term of the core explanatory variable is positive and the second power term is negative. This result shows that the impact of the progress of digital technology in the service industry on carbon emissions is a nonlinear relationship, showing a trend of first promoting and then restraining, which strongly supports the hypothesis. It also indicates that the development of digital technology can be an important way to solve the carbon emission in the service industry.

5.2. Robustness tests and endogeneity tests

In order to ensure the validity of the benchmark regression results, this paper discusses them from the perspectives of robustness. In terms of robustness, this paper adopts two approaches. The first method is winsorization treatment. From the point of view of data, we

Table 1
Variable symbols and calculation methods.

Variable	Variable Name	Variable Symbol	Calculation Method
Explanatory Variable	Carbon Emission Intensity	*lnco*$_2$	$ln\ co_2 = \ln(CO_{2itf} + 1)$
Core Explanatory Variables	Degree of Digital Technology	*EIE*	Frequency of occurrence of terms such as “artificial intelligence”, “blockchain”, “big data”, “cloud computing”, “digital technology” and other keywords in the annual reports of service companies by province (1000)
Control variable	Number of People Working	*NE*	Number of people working in a particular service industry in a given year in a specific province (10,000)
	Urbanization Rate	*DU*	Urbanization rate of a province in a given year (%)
	Development of Service Industry	*DTI*	Value added of service industry by province (hundreds of billions of yuan)
	Population Density	*DP*	Number of permanent residents/area of provinces (thousands persons/km^2)
	Educational Level	*EDU*	Number of students enrolled in higher education (10,000)
	Fiscal Decentralization	*FPD*	Local government revenue (expenditure)/central government revenue (expenditure)
	Level of Economic Development	*EDL*	GDP per capita (million yuan/person)
	Internet Penetration	*IP*	Number of computers in use per 100 population (units)
	Degree of Population Growth	*DPG*	Natural population growth rate (%)

Table 2
Descriptive statistics of variables.

Variable	Number of Statistics	Minimum Value	Maximum Values	Average Value	Standard Deviation
lnco$_2$	4860	0	27.130	18.843	4.396
EIE	4860	0	7.671	0.040	0.254
NE	4860	0	1053.500	62.626	104.061
DU	4860	0.291	0.896	0.557	0.133
DTI	4860	0.443	60.268	9.358	8.788
DP	4860	0.649	5.967	2.812	1.193
EDU	4860	4.220	231.970	81.781	48.499
FPD	4860	0.001	0.066	0.017	0.013
EDL	4860	0.970	16.178	4.354	2.416
IP	4860	0	72	13.460	14.691
DPG	4860	−1.010	11.470	5.250	2.672

Table 3
Benchmark model results.

Dependent variable →	lnco$_2$				
Explanatory variables ↓	M_1	M_2	M_3	M_4	M_5
Independent Variable					
EIE	0.934*** (0.128)	1.995*** (0.313)	1.418*** (0.299)	1.546*** (0.312)	1.449*** (0.306)
EIE^2		−0.223*** (0.054)	−0.139*** (0.047)	−0.156*** (0.049)	−0.138** (0.071)
Control Variable					
DP			−0.002*** (0.056)	−0.005*** (0.056)	0.052 (0.059)
EDU			0.021*** (0.002)	0.021*** (0.002)	0.021*** (0.003)
DPG			−0.249*** (0.024)	−0.248*** (0.024)	−0.190*** (0.032)
NE				−0.001 (0.000)	−0.001** (0.000)
DU					0.296 (1.133)
DTI					−0.084*** (0.022)
FPD					55.052*** (14.451)
EDL					0.132* (0.067)
IP					−0.017* (0.009)
Time	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES
R^2	0.006	0.010	0.114	0.115	0.120
F	14.734***	9.929***	78.949***	65.890***	39.869***

Note: ***, ** and * denote 1%, 5% and 10% significance levels, respectively.

winsorize bilaterally for variables below 1% and above 99% of all continuous data and the specific results are shown in columns M_1 in Table 4. It is not difficult to find that the primary term of the carbon emission intensity of the service industry and the degree of digital technological $(EIE, M_1, r = 1.549, p < 0.01)$ is still positive at the 1% significant level and the second power term of the degree of digital technology $(EIE^2, M_1, r = -0.155, p < 0.05)$ is still negative at the 5% significant level after the shrinking tail treatment. This result is consistent with the benchmark regression results, indicating the robustness of the benchmark regression results.

The second method is excluding some samples. From the perspective of the actual sample, this paper finds that there is a 0-value phenomenon in the carbon emissions of the service industry in some provinces. And the existence of this phenomenon means that there may be statistical errors in the data, so that the sample data and the overall data show non-consistency. Therefore, this paper chooses to exclude this type of sample in the process of the robustness test and regresses the data again. The regression results are shown in column M_2 in Table 4. After excluding some samples, there is a positive correlation between the carbon emission intensity of the service industry and the first power term of the digital technology degree $(EIE, M_2, r = 1.662, p < 0.01)$, and a negative correlation between the carbon emission intensity and the second power term $(EIE^2, M_2, r = -0.191, p < 0.01)$. Therefore, the relationship between carbon emission intensity of service industry and the degree of digital technology is inverted U-shaped, indicating that the results of benchmark regression are robust.

5.3. Endogeneity tests

In terms of Endogeneity, this paper adopts two approaches. First, this paper refers to the practice of Chen and Liu (2022) [83] and adds control variables to the benchmark regression model in order to solve the endogeneity problem caused by missing variables. In

Table 4
Results of robustness tests and endogeneity tests.

Test Items	Winsorization	Exclusion of Some Samples	Addition of Control Variables	Replacement of Lagged variable	GMM Regression		
Dependent Variable →	$lnco_2$		$lnco_2$				
Explanatory Variables ↓	M_2	M_4	M_3	M_4	M_5	M_6	M_7
					t-1	*t-2*	*t-1& t-2*
Independent Variable							
EIE	1.549*** (0.332)	1.662*** (0.268)	1.742*** (0.561)		1.578*** (0.323)	13.321** (6.183)	7.881** (3.262)
EIE^2	−0.155** (0.051)	−0.191*** (0.041)	−0.191* (0.100)		−0.165*** (0.048)	−1.982** (0.949)	−1.148** (0.503)
EIE_{t-1}				1.319** (0.517)			
EIE_{t-1}^2				−0.178* (0.095)			
Instrumental Variable					YES	YES	YES
Control Variable	YES	YES	YES	YES	YES	YES	YES
Time	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES	YES
N	4860	4742	4860	4410	3060	3060	3060
Wald value					583.731***	43.944***	148.332***
R^2	0.120	0.064	0.127	0.190	0.123	0.054	0.112

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively; *t-1* denote that the variables lagged one period are used; *t-2* denote that the variables lagged two periods are used; *t-1& t-2* denote that the variables lagged one period and lagged two periods are used at the same time.

this paper, forest area [37] and railway transportation mileage [84] are added to the model, and the benchmark model is regressed again. The results show that the relationship between the digital technology degree and the carbon emission intensity of the service industry is still inverted U-shaped $(EIE, M_3, r = 1.742, p < 0.01$ & $EIE^2, M_3, r = -0.192, p < 0.1)$.

Secondly, referring to the practice of Xu et al. (2022), this paper uses lagged variables to solve the endogeneity problem [85]. (1) The lagged variable replacement. Since there may be a bidirectional causal relationship between the carbon emission intensity of the service industry and the digital technology degree, this paper uses the digital technology degree lagged by one period to replace. The results show that the carbon emission intensity of service industry and the first power term of the digital technology degree lagged by one period was significantly positive correlation $(EIE_{t-1}, M_4, r = 1.319, p < 0.05)$. And it is significantly negatively correlated with the second power term of the digital technology degree lagged by one period $(EIE_{t-1}^2, M_4, r = -0.178, p < 0.1)$. This result is consistent with the benchmark regression results. (2) GMM regression. Since this paper uses word frequency to measure the digital technology degree, it is inevitable that there is a measurement error between the word frequency and the unobservable real value. In this paper, the digital technology degree lagged by one period and two periods is used as the instrumental variable for GMM regression. The specific results are shown in columns M_5, M_6 and M_7 in Table 4. The results are consistent with the benchmark regression results, which further illustrates the robustness of the benchmark regression results.

5.4. Threshold effect analysis

After the discussion above, there is an inversed U-shaped relationship between CESI and the degree of digital technology. There may be a threshold effect between them. Therefore, this paper designs a threshold effect model to further study it. Based on the results of the benchmark regression, there is a single-threshold effect between the explanatory variables and the core explanatory variables, and the single-threshold model is designed as follows:

$$ln\ co_{2itf} = \beta_0 + \beta_1 EIE_{itf} I(Q_{itf} \le q) + \beta_2 EIE_{itf} I(Q_{itf} > q) + \beta_3 control_{itf} + \gamma_i + \delta_t + \eta_f + \varepsilon_{itf} \tag{9}$$

EIE is the threshold dependent variable and the core explanatory variable; $I(\cdot)$ is the schematic function; Q is the meaning of threshold

Table 5
Threshold effect existence results.

Explanatory Variable	Core Explanatory Variables	Model	F-value	P-value	Threshold Estimate	95% Confidence Interval
	EIE	Single Threshold	9.900**	0.043	0.060	[0.042,0.064]
$lnco_2$	*EIE*	Double Threshold	3.840	0.533	–	–
	EIE	Three Thresholds	2.330	0.780	–	–

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively.

variable, and *EIE* is the threshold variable. The meaning of other variables is the same as the meaning of Equation (7). If there is a multi-threshold effect, double-threshold model and triple-threshold model are utilized for analysis.

Threshold existence and threshold truthfulness tests are required before conducting threshold regression. This paper uses *Stata* software, using the self-sampling method to repeatedly sample 300 times to determine the number of thresholds and test the significance of the number of thresholds. As shown in Table 5, the single-threshold test of the *F*-value is 9.900 and *P* value is 0.043 when using carbon emission intensity ($ln\ co_2$) as the explanatory variable and the degree of digital technology (*EIE*) as the core explanatory variable, indicating that the original hypothesis that there is no threshold effect is rejected at the 5% significance level. Thus, there is a single threshold effect. Similarly, the double and triple threshold tests are conducted when taking $ln\ co_2$ as the explanatory variables and *EIE* as the core explanatory variables, and the results show that the *F*-values are 3.840 and 2.330 respectively, and the *P*-values are 0.533 and 0.780 respectively, which do not pass the significance test. Therefore, there is no double-threshold effect and triple-threshold effect. This test result is also consistent with the results of the benchmark regression, indicating that there is indeed a single-threshold effect between carbon emissions in the service industry and the degree of digital technology.

Additionally, the grid search method was used to determine the threshold estimates with extremely 95% confidence intervals to further determine the veracity of the thresholds. From Table 5, it is easy to find that its single threshold estimate is 0.060 with a 95% confidence interval of $[0.042, 0.064]$.

Table 6 shows the results of the threshold regression of the degree of digital technology in the service industry on carbon emission intensity after controlling the control variables. This result is also presented in Fig. 4. The following results are obtained: When the threshold variable satisfies $Q \leq q$, the influence coefficient of core explanatory variable *EIE* on the carbon emission intensity ($ln\ co_2$) of the service industry is 2.173, which is significant at the significance level of 1%. However, when the threshold variable $Q > q$, the influence coefficient of the core explanatory variable *EIE* on the carbon emission intensity ($ln\ co_2$) of the service industry is -0.913, which is significant at the significance level of 1%. It can be seen that when the degree of digital technology in the service industry is less than the threshold, it presents a facilitating effect on the carbon emissions of the service industry. Once when the degree of digital technology in the service industry is greater than the threshold, it presents a suppressing effect on the carbon emissions of the service industry. In addition, it should be pointed out that when the degree of digital technology exceeds the threshold value, the suppression effect of digital technology on carbon emissions of the service industry is slow ($|\beta_1| > |\beta_2|$). Therefore, digital technology does have a suppressing effect on CESI in practice, but this suppressing effect is weaker than the promoting effect. And the role of digital technology on CESI needs to be carefully examined.

5.5. Mechanism tests

With the development of digital technology, on the one hand, the digital technology itself facilitates the implementation of carbon emissions trading pilots and carbon markets. On the other hand, the market mechanism continues to evolve to incorporate the impact of digital technology on the service industry into the scope of regulation. In this process, the government's constraints on the development of digital technology in the service industry through policy instruments and the limitation of carbon emissions play a role as a mechanism from it. Therefore, this paper assesses the role of policy through DDD method.

The DDD method is based on the difference-in-difference (DID) method, and further proposes the difference between the experimental group and the control group, so as to obtain more accurate results compared with DID model. On November 4, 2011, the National Development and Reform Commission held a kick-off meeting for China's carbon emissions trading pilot work in Beijing, identifying seven provinces and municipalities, namely, Beijing, Guangdong, Shanghai, Tianjin, Hubei, and Shenzhen, as the first batch of carbon emissions trading pilot provinces and municipalities. In 2013, the carbon emissions trading markets in the seven provinces and cities opened one after another, and the exploration of the carbon market not only focuses on heavy industries such as the power industry, but also takes service industries such as civil aviation into consideration. For example, wholesale and retail, transportation and other service industries in developed service areas such as Shanghai and Shenzhen are also included in the scope of the carbon market. Thus, 2013 is taken as the starting point for the policy to work. This paper believes that the role of the carbon market is more obvious for high-pollution and high-emission industries [86]. Therefore, high carbon emission service industries such as transportation industry in pilot provinces are selected as the experimental group of the DDD model. Based on the above analysis, this paper obtains DDD model for mechanism testing as follows:

$$ln\ co_{2itf} = \beta_0 + \beta_1 pilot_f \times post_t \times pollution_i + \beta_2 pilot_f \times post_t + \beta_3 post_t \times pollution_i + pilot_f \times pollution_i + \beta_3 control_{itf} + \gamma_i + \delta_t + \eta_f + \varepsilon_{itf}$$

The dummy variable of the policy pilot area is denoted by $pilot_f$, which indicates that when the province f is the pilot province, the $pilot_f$ takes the value of 1, otherwise it takes the value of 0. The policy pilot time dummy variable is denoted by $post_t$ to indicate that after 2013, the value of $post_t$ is 1, and 0 otherwise; the industry pollution attribute dummy variable is denoted by $pollution_i$ to indicate that when the industry i belongs to high carbon emission service industry such as transportation industry, it takes the value of 1, otherwise it takes the value of 0. The main focus of the model is on the interaction term $pilot_f \times post_t \times pollution_i$, so it is taken as the core explanatory variable. The meanings of the remaining variables are the same as in Equation (7).

The regression results of DDD are obtained as shown in Table 6. From The results show that no control variables were introduced in M_3 in order to visually test the impact of policies on CESI, while controlling for time, industry, and province fixed effects. And the regression results are found to be significantly negative at the 5% level of significance. Subsequently, control variables are added to the model, and the regression results in M_4 are found to be significantly negative at the 5% significance level. This also means that the pilot

Table 6
Regression results of further studies.

Variable	*lnco*$_2$			
	M_1	M_2	M_3	M_4
EIE ($Q \leq q$)	2.173*** (0.848)			
EIE ($Q > q$)		−0.913*** (0.311)		
$pilot_f \times post_t \times pollution_i$			−0.520** (0.251)	−0.496** (0.245)
control variable	YES	YES	NO	YES
Time	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Province	YES	YES	YES	YES
N	3829	1031	4860	4860
R^2	0.089	0.089	0.021	0.021

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively.

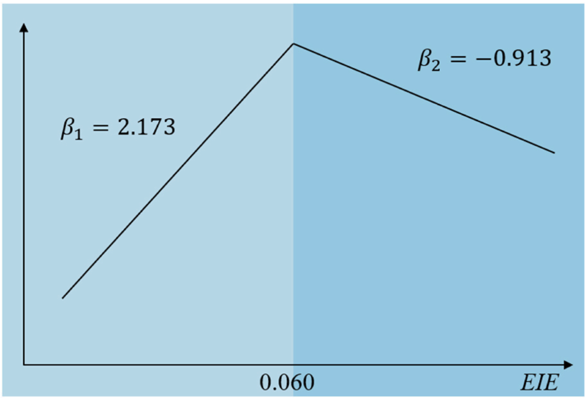

Fig. 4. The results of threshold regression.

policy of carbon market has reduced CESI by 173.17 Mt[4] and CESI per 10,000 people by 0.0065 Mt[5] in the pilot cities of China. Therefore, China's carbon emission market policy has a repressive effect on CESI, and the constraints of government policy have a repressive effect in the process of digital technology affecting CESI.

5.6. *Heterogeneity tests*

This paper analyzes the heterogeneity from the perspectives of resource endowment differences, regional differences and industrial structure industries. China has a vast territory, and there are obvious differences in resource endowment, economic development level and industrial structure. Therefore, this paper further deepens the research from these three perspectives.

In terms of resource endowment heterogeneity, the distribution of resources in China is characterized by uneven regional distribution, which leads to differences in resource endowments in various regions. This difference brings about differentiated impacts, on the one hand, regions with resource-rich endowment may have the "Resource Curse effect" [87], so that too much development resources flow to energy-based services, resulting in regions in the process of development produces more carbon emissions. However, due to the lack of innate resource advantages, regions with poor- resource endowments pay more attention to non-energy service industries. The development of digital technology further reduces its dependence on energy. Therefore, the development of digital technology reduces carbon emissions. On the other hand, considering the government's role in development, there is an inverted relationship between resource distribution and carbon emissions. For example, regions with resource-rich endowments receive more attention from the government, but pay more attention to the regulation of carbon emissions. However, the carbon emissions of regions with resource-poor endowment receive less attention from the government than those with resource-rich endowment. In addition to the progress of modern transportation technology, the disadvantage of uneven spatial distribution of resources is further

[4] $CESI_1 = TCESI \times (e^{\beta_1} - 1)$. $CESI_1$ means *CESI* that have been reduced in the pilot cities of China. *TCESI* means total *CESI* in the pilot cities of China, which is taken from 2019 as an example.

[5] $CESI_1 = TCESI \times (e^{\beta_1} - 1)/TP$. $CESI_1$ means *CESI* that have been reduced in the pilot cities of China. *TCESI* means total *CESI* in the pilot cities of China, which is taken from 2019 as an example. *TPN* means the total population in the pilot cities of China, and the unit is 10,000 people.

reduced. On the contrary, digital technology in regions with resource-rich endowment promotes CESI, while digital technology in regions with resource-poor endowment reduces the carbon emissions of the service industry. Therefore, based on the above analysis, it is necessary to analyze the heterogeneity according to the differences in regional resource endowment distribution.

This paper classifies places based on resource endowment as measured by regional resource production [88],[6] and obtain the regression results as shown in Table 7. When *EIE* and EIE^2 are introduced only, the results are significant at 1% significance level for resource-poor regions. However, after the introduction of control variables, EIE^2 becomes insignificant ($EIE^2, M_3, r = -0.025, p > 0.1$), and the significance of *EIE* decreases ($EIE, M_3, r = 0.704, p < 0.1$). After the exclusion of EIE^2, the coefficient of *EIE* is positive at 1% level of significance ($EIE, M_4, r = 0.578, p < 0.01$). Therefore, the degree of digital technology shows a positive correlation with CESI for the resource-poor regions. Similarly, *EIE* for resource-rich areas is positive at the significance level of 1% ($EIE, M_7, r = 1.834, p < 0.01$) and EIE^2 is negative at 1% significance level ($EIE^2, M_7, r = -0.214, p < 0.01$) after adding *EIE*, EIE^2 and control variables. Therefore, the relationship for resource-rich regions between CESI and the digital technology is inversed U-shaped. This also indicates it is not only necessary to pay attention to the regions with resource-rich endowment, but also should pay attention to the regions with resource-poor endowment especially in the process of solving the problem of CESI by using digital technology, so as to avoid the formation of a positive feedback loop.

In terms of regional heterogeneity, regional differences affect the degree of development of digital technology and the development pattern of the service industry, which in turn has a differential impact on regional carbon emissions. Therefore, this paper examines regional heterogeneity. According to the concept of economic geography, this paper divides the study area into the eastern region[7], the central region[8], the western region[9] and the northeastern region[10]. And the specific analysis results are shown in Table 8. The results show that the regression results of the eastern, central, western and northeastern regions all meet the *EIE* regression coefficient of the first power term is positive, and the second power term EIE^2 regression coefficient is negative, which is generally consistent with the benchmark regression results. However, the results of the eastern region and the northeastern region show that the second power term EIE^2 is not significant ($EIE^2, M_1, r = -0.072, p > 0.1$ & $EIE^2, M_5, r = -4.942, p > 0.1$). Further analysis shows that there is a significant positive correlation between carbon emissions and *EIE* in the eastern and northeastern regions ($EIE, M_2, r = 0.712, p < 0.01$ & $EIE, M_6, r = 4.204, p < 0.01$). Therefore, the development of digital technology in the eastern and northeastern regions promote regional carbon emissions, and management should be tailored to the development characteristics of different regions.

Due to differences in production factors, geographical location and other factors, the industrial structure of different regions also varies. Heavy industry has an obvious spillover effect on the service industry. And the different development levels of heavy industry have an impact on the carbon emissions of the service industry. Therefore, this paper classifies and analyzes the differences in industrial structure. This paper calculates the ratio of the added value of the output value of the secondary industry to the added value of the output value of the tertiary industry (*the added value of the output value of the secondary industry* / *the added value of the output value of the tertiary industry*) to describe the industrial structure [89]. When the value is greater than the average, this paper considers that the region focuses on the secondary industry. Otherwise, the region focuses on the tertiary industry. The results are shown in Table 9. For regions focusing on the secondary industry, the degree of digital technology promotes a significant increase in the carbon emissions intensity ($EIE, M_2, r = 0.840, p < 0.05$), and there may be a quite strong correlation effect between the secondary industry and the tertiary industry. Therefore, different industrial structures have different impacts on the impact of digital technology on CESI.

Few existing studies have focused on the relationship between carbon emissions and digital technologies in the service industry. Based on this realistic problem, this paper focuses on revealing the relationship between digital technology and carbon emissions of the service industry. This paper examines this overall relationship by using a benchmark regression model that includes both EIE and EIE.[2] In order to further understand the specific relationship between CESI and digital technology, this paper sets a single threshold effect model to test it. The results show that digital technology first rapidly promotes the increase of CESI and then slowly promotes the decrease of CESI. This paper hopes to answer the core question of whether the service industry improves environmental problems in the process of digital transformation, that is, reduce CESI. The answer is yes. Digital technology can promote the development of service enterprises and reduce CESI. The main findings are shown in Fig. 5.

Faced with the reality that many countries and regions are in the initial stage of carbon market and the carbon market focuses on the manufacturing industry but ignores the service industry, this paper also tests the mechanism of carbon market pilot policy. This paper sets up the DDD model to test the impact of the carbon market pilot policy in 2013 on the service industry. The results show that the carbon market pilot policy has an important carbon emission reduction effect on the service industry. Therefore, it is necessary to build a more complete and comprehensive carbon market. Moreover, this paper analyzes the possible impacts of differences in resource endowment, regional differences and industrial structure through heterogeneity test. The results show that the impact of digital technology on CESI is indeed affected by these heterogeneous factors. Therefore, the government needs to implement the digital

[6] According to Cui et al. (2013), Liaoning, Guangdong, Shandong, Xinjiang, Sichuan, Yunnan, Inner Mongolia, Anhui, Jiangxi, Shanxi, Heilongjiang, Henan, Hunan, and Shaanxi are treated as resource-rich areas, and Hebei, Jiangsu, Zhejiang, Fujian, Beijing, Tianjin, Shanghai, Hainan, Guizhou, Gansu, Qinghai, Jilin, Hubei, Guangxi, Chongqing, and Ningxia are treated as resource-poor regions.

[7] The Eastern Region includes Hebei Province, Beijing, Tianjin, Shandong Province, Jiangsu Province, Shanghai, Zhejiang Province, Fujian Province, Guangdong Province, Hainan Province, Taiwan Province, Hong Kong Special Administrative Region, and Macao Special Administrative Region.

[8] Central region including Shanxi, Henan, Anhui, Hubei, Jiangxi and Hunan provinces.

[9] The western region includes Chongqing, Sichuan, Yunnan, Guizhou, Tibet Autonomous Region, Shaanxi, Gansu, Qinghai, Xinjiang, Ningxia Hui Autonomous Region, Inner Mongolia Autonomous Region and Guangxi Zhuang Autonomous Region.

[10] The Northeast region includes Heilongjiang, Jilin and Liaoning Provinces.

Table 7
Analysis of resource heterogeneity.

Variable	Non-resource-rich Regions				Resource-rich Regions		
Dependent Variable →	*lnco₂*						
Explanatory Variables ↓	M_1	M_2	M_3	M_4	M_5	M_6	M_7
Independent Variable							
EIE	1.012***	1.843***	0.704*	0.578***	0.770***	1.728***	1.834***
	(0.162)	(0.427)	(0.385)	(0.056)	(0.170)	(0.434)	(0.480)
EIE^2		−0.171***	−0.025			−0.204**	−0.214***
		(0.077)	(0.057)			(0.068)	(0.073)
Control Variable	NO	NO	YES	YES	NO	NO	YES
Time	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES	YES
N	2268	2268	2268	2268	2592	2592	2592
R^2	0.007	0.011	0.142	0.143	0.004	0.008	0.106
F	8.946***	5.321***	21.428***	23.577***	5.058***	3.520***	19.090***

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively.

Table 8
Analysis of regional heterogeneity.

Variable	Eastern Region		Central Region	Western Region	Northeastern Region	
Dependent Variable →	$lnco_2\_EAST$		$lnco_2\_CEN$	$lnco_2\_WEST$	$lnco_2\_NE$	
Explanatory Variables ↓	M_1	M_2	M_3	M_4	M_5	M_6
Independent Variable						
EIE	1.079** (0.528)	0.712*** (0.228)	11.904*** (4.224)	17.128*** (5.743)	5.319* (3.154)	4.204*** (1.403)
EIE^2	−0.072		−15.773*	−13.458**	−4.942	
	(0.093)		(9.408)	(6.567)	(13.523)	
Time	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Province	YES	YES	YES	YES	YES	YES
N	1620	1620	972	1782	486	486
R^2	0.194	0.194	0.072	0.087	0.037	0.047
F	35.168***	38.635***	6.742***	15.242***	9.578***	10.547***

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively.

Table 9
Analysis of the heterogeneity of industrial structure.

Variable	Regions focusing on the secondary industry		Regions focusing on the tertiary industry	
Dependent Variable →	$lnco_2$			
Explanatory Variables ↓	M_1	M_2	M_3	M_4
Independent Variable				
EIE	1.469* (0.756)	0.840** (0.360)	0.593 (0.835)	0.440 (0.341)
EIE^2	−0.123		−0.030	
	(0.131)		(0.149)	
Control Variable	YES	YES	YES	YES
Time	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Province	YES	YES	YES	YES
N	2916	2916	1944	1944
R^2	0.1882	0.1882	0.1843	0.1847
F	28.420***	31.174***	19.823***	21.811***

Note: ***, **, * denote 1%, 5% and 10% significance levels, respectively.

transformation policy of service industry according to local conditions and the actual situation.

The theoretical contributions of this paper are as follows: (1) This paper focuses on the carbon emissions of the service industry and the solution of the carbon emissions problem. This is something that the existing literature has paid less attention to. In the wave of digitalization, the development effect and environmental effect of digital technology on the service industry can exist simultaneously. Therefore, it is feasible to firmly promote the digital transformation of the service industry. (2) This paper extends the research on carbon markets. The research pays more attention to the impact of carbon market on the manufacturing industry at present, while this

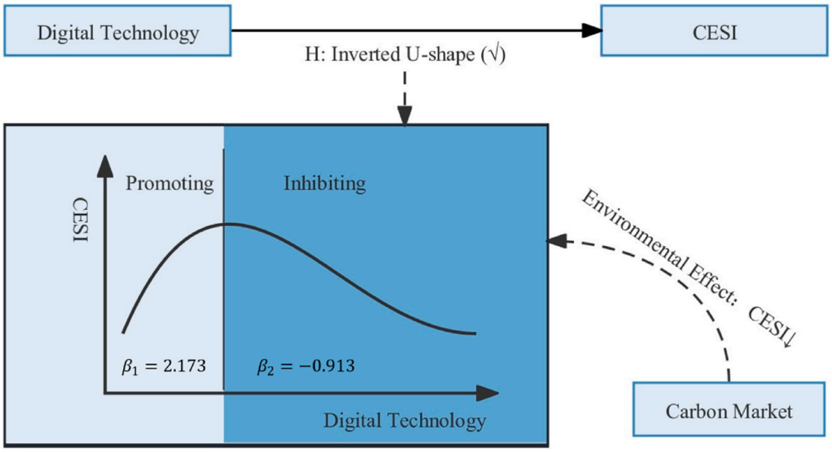

Fig. 5. Main findings.

paper further extends the impact to the service industry. The construction of carbon market can promote the reduction of CESI. The results reveal the need to promote the construction of carbon markets. (3) This paper is an extension of EKC theory. This paper uses digital technology as a proxy variable to study CESI, which further expands the research on environmental Kuznets curve. For China, the country with the highest carbon emissions, the inverted U-shaped relationship between CESI and digital technology is extremely important. This study further supports the feasibility of China's carbon emission reduction and provides a path for China's carbon emission reduction.

6. Discussion

This research result supports the view that digital technology and reasonable policy measures can affect corporate carbon emissions, and extends the EKC theory. Specifically, this study verifies the relationship between the digital technology, policy instruments and CESI in a theoretical and empirical way. First, more advanced digital technologies are substantially related to carbon emissions in the service industry. Different from the technology emphasized by previous studies [90], this paper focuses on the role of digital technology. The study further confirms the promotion effect of digital technology on enterprise development and the threshold effect on carbon emissions. This means that the process of using digital technology to promote the development of service enterprises is conducive to the realization of national and enterprise carbon emission reduction goals, and the development path is feasible. However, different from the existing research, this paper pays more attention to the development of service enterprises. Different from the research of Yang et al. (2023), service enterprises are different from manufacturing enterprises in terms of the degree of integration of digital technology, the correlation effect of the industry, the R&D capability of technology and the relationship with consumers [37]. This research contributes to the further expansion of the role of digital technology.

Second, more reasonable policy instruments dominate CESI. Research on policy means such as carbon tax, carbon price, carbon quota and carbon market has revealed their guiding role in industrial development [40–43]. Reasonable policy measures can correct corporate behaviors and better fulfill corporate responsibilities. However, the results focus on carbon market policies, especially in China, where the construction of carbon market is relatively immature. The results reveal the feasibility of including service sector firms in the construction of carbon markets. This result further affirms the important role of carbon market policy in the regulation and sustainable development of the service industry [50].

Third, the results extend the EKC theory. Since Grossman and Krueger (1991) propose this theory [91], EKC is used in the discussion of environmental issues [92]. EKC theory believes that with the growth of the economic development level of a country or region, the change trend of environmental pollution is first up and then down. Although many studies believe that this relationship does not exist [93,94], the research confirms that this relationship does exist in China's service industry and supports the view that EKC exists in countries with high carbon emissions [95]. Specifically, this paper uses the level of digital technology development as a proxy variable for the level of economic development and the level of carbon emissions as a proxy variable for environmental pollution to test the existence of EKC theory in China. This practice also incorporates digital technology into EKC theory and expands the scope of proxy variables. Additionally, under the framework of EKC theory, Yao et al. (2021) believe that natural resource rents lead to government corruption and thus lead to the failure of EKC theory [96]. However, the results in this paper put forward a different point of view from the perspective of government attention and government regulation, and believe that this inverted U-shaped relationship still exists.

7. Conclusion and recommendation

7.1. Conclusion

Based on the perspective of digital transformation of the service industry, this paper explains and examines the relationship between carbon emissions and digital technology in the service industry from both theoretical and empirical perspectives, and further investigates the effect of the inverted U-shaped curve. The conclusions show that:

(1) Overall, there is an inverted U-shaped relationship between CESI and the digital technology. Carbon market and pilot policy play a role of suppressing in the impact of digital technology and CESI.
(2) When the development of digital technology reaches the threshold, the digital technology significantly inhibits CESI, and this inhibiting effect is weaker than the promoting effect.
(3) In terms of resource heterogeneity, there is an inversed U-shaped relationship between CESI and the digital technology degree in better endowed regions such as Liaoning and Guangdong. In poorly endowed regions such as Beijing and Tianjin, the digital technology significantly promotes CESI. In terms of regional characteristics, the relationship between carbon emissions and digital technology in the eastern and northeastern regions is different from that in other regions. Furthermore, the difference in industrial structure makes the effect of digital technology different.

7.2. Policy implication

The conclusions of this paper have implications for policy making in China and other countries. The policy implications are as follows:

(1) Service enterprises should further promote digital transformation. Although the large amount of carbon emissions generated by digital transformation in the early stage is not conducive to the realization of carbon emission reduction, the digital transformation of service enterprises is conducive to improving the competitiveness and management level of enterprises in the long run. Service enterprises can realize the green and low-carbon transformation of the whole industrial chain. In the process of digital transformation of the service industry, resources such as tax policy, subsidy policy and financial system should be fully integrated. Establishing an Internet platform in line with the development of enterprises and enhancing the integration of data resources and physical capital can promote the sustainable development of enterprises.
(2) The government should use policy approaches to promote the digital transformation of service enterprises in a hierarchical and orderly manner and the construction of carbon market. Promoting the digital transformation of the whole industry, especially the service industry will undoubtedly increase the environmental pressure in a balanced manner in a short period of time. Therefore, utilizing carbon tax, carbon price and national planning to promote enterprises to reasonably promote digital transformation are necessary. Service enterprises with relatively poor infrastructure configuration and immature growth should shift their development focus to enterprise growth rather than digital transformation according to policy guidance such as subsidies for small and medium-sized enterprises. The government should implement the policy arrangement concept of combining top-level design with regional collaborative governance. Moreover, China's carbon market construction is in its initial stage. It is necessary to optimize the energy mix, accelerate the development of digital talent, and highlight the role of the financial system in the development of carbon markets.
(3) Emerging countries should balance the roles of the government and the market. The role of the government in the early stage of national carbon reduction is undoubtedly crucial. The government gives full play to its functions and promotes the construction of a national digital platform, digital technology and digital industry. The role of the Internet and data in national governance and business development should also be emphasized. Administrative and legal approaches can be used to guide the flow of national funds, cultivate digital talents, build digital evaluation system and prevent platform enterprises from monopolizing. Furthermore, market mechanisms, especially carbon markets, should be planned in time. The market gradually frees from the constraints of the government and plays a leading role in the development of service enterprises, and operates according to the market rules. According to the characteristics of national development, emerging countries can better use the means of administrative intervention and market mechanism to promote the carbon emission reduction of enterprises, especially in the service industry.

7.3. Limitation and future recommendation

Due to the problems in data acquisition, this paper only selects the data before 2020 to test the impact of digital technology on CESI. As the service industry is the most severely affected by COVID-19, it is necessary to consider the impact of digital technology on CESI under the impact of the epidemic. EDGAR report[11] also shows that carbon emissions in 2020 are significantly lower than those in 2019 and 2021, and the analysis attributes that to COVID-19. The recommended approach is to use the COVID-19 emergency as the

[11] URL: https://edgar.jrc.ec.europa.eu/report_2021#data_download.

mechanism for considering its impact on digital technology and on CESI. Such an approach could yield policy recommendations closer to the post-pandemic era.

It is worth noting that the study of carbon emissions changes after 2020, especially in the service industry, needs to exclude the impact of the COVID-19. As COVID-19 has an impact on employment, psychology and so on, future research can consider the labor force as an important mechanism to analyze the impact of digital technology on carbon emissions. In addition, it is also an interesting research direction to collect data in the form of questionnaires and analyze the impact of labor force psychological changes before and after the impact of COVID-19 on carbon emissions in the service industry.

In the heterogeneity test, this paper finds that industrial structure makes the effect of digital technology different. For reasons of limited space, this paper does not discuss the industrial structure in detail. In China and most emerging countries, the contribution of the secondary industry to the whole country is very prominent. Therefore, it is necessary to discuss the industrial structure. In the future research, the impact of industrial structure on digital technology and CESI can be further discussed, and the correlation effect between the service industry and other industries should be considered, particularly.

Additionally, the construction of China's carbon market is still in the initial stage of development, and how to integrate the service industry into the process of carbon market construction needs further research. This has important implications for the construction of carbon markets in emerging countries.

Although this paper concludes that the progress of digital technology can promote CESI, there are also some problems that need to be paid attention to in reality. For example, the development characteristics and dominant industries of different regions need to be taken into account in the policy making process. Overemphasizing the carbon emission reduction effect of digital technology on the service industry will only make the region lose its comparative advantage and the ability of regional cooperation, which is not conducive to the development of the overall economy. All in all, only by accurately grasping the current situation of regional development and combining digital technology with the law of CESI can regional economy be better promoted to develop towards a green and sustainable direction.

Fundings

This research is supported by National Key R&D Program of China (2023YFC3804901), The National Social Science Fund of China (No. 22BJY099), Jiangsu Social Science Fund (No. 22EYA003), and China National University Student Innovation & Entrepreneurship Development Program (No. 202310286083Z).

Data availability statement

The data in the paper are available on request from the corresponding author.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Keyang Zhan: Writing – original draft, Software, Methodology. **Zhengning Pu:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Zhengning Pu reports financial support was provided by National Key R&D Program of China. Zhengning Pu reports financial support was provided by The National Social Science Fund of China. Zhengning Pu reports financial support was provided by Jiangsu Social Science Fund. Keyang Zhan reports financial support was provided by China National University Student Innovation & Entrepreneurship Development Program. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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