Technological Forecasting & Social Change 187 (2023) 122236

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Integrated development of digital and energy industries: Paving the way for carbon emission reduction

Jiangquan Wang [a,b], Xuan-Hoa Nghiem [c], Fauzia Jabeen [d], Adeel Luqman [e], Malin Song [f,*]

[a] School of Economics, Fujian Normal University, Fuzhou 350117, China
[b] School of Ecological Environment and Urban Construction, Fujian University of Technology, Fuzhou 350118, China
[c] Faculty of Economics and Management, International School, Vietnam National University, Hanoi, Viet Nam
[d] College of Business, Abu Dhabi University, United Arab Emirates
[e] Research Institute of Business Analytics and Supply Chain Management, College of Management, Shenzhen University, Shenzhen 518060, China
[f] School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu 233030, China

ARTICLE INFO

JEL classification:
O33
Q40
Q49

Keywords:
Digital industry
Energy industry
Fusion
Evaluation index system
Influence factor

ABSTRACT

The fusion of digital and energy industries is an efficacious route to advance the high-quality development of the energy system and ensure energy security. This study explored the fusion mechanism of digital and energy industries and built an evaluation index system for the fusion of digital and energy industries from four dimensions: fusion basis, fusion conditions, fusion application, and fusion performance. Next, the fusion level of digital and energy industries and their performance in different dimensions in China and various regions were calculated using the global principal component analysis. Subsequently, the panel data model was used to quantitatively study the influence factors of the integrated development of China's digital and energy industries. The study revealed that the fusion level of China's digital and energy industries has continuously improved from 2002 to 2018, but the gap between different regions in 2017 was still large. The integrated development of digital and energy industries is positively correlated with the development level of digital and energy industries, scientific and technological innovation, environmental regulation, and urbanization.

1. Introduction

Owing to rapid economic and social development, many countries or regions are encountering increasing constraints on resources, energy, and the environment—a common issue being the deficit of ecological environment (such as climate change) caused by carbon emissions, energy development, and utilization (Doğan et al., 2021; Shahzad et al., 2022). The economic growth model based on over-reliance of factor investment and scale expansion has failed to meet the requirements of sustainable development (Zhao et al., 2022a). Hence, there is an urgent need to transform the economic development mode into a high-quality growth mode, such as a circular economy paradigm (Q. Zhang et al., 2022), by optimizing the economic structure and changing the driving force of growth. Green technology is one of the important ways to solve certain environmental problems (Ashfaq et al., 2022), with electrification, decarbonization, and digitization as three major trends in the development of energy systems (Bañales, 2020).

Sustainability is receiving more attention due to the COVID-19 pandemic (Khan et al., 2022). Sustainable energy development is the inevitable choice for human survival (Arachchi and Managi, 2021), and it is every country's goal. Energy security (ES), energy efficiency (EE), and their influencing factors have been widely studied by scholars. Song and Tao (2021) measured the regional ES level in China and discussed its influence factors by applying the spatial lag model. The results indicated that although ecological environment, energy production, and technological progress promote ES, population size and energy consumption intensity harm regional ES. Li et al. (2019) studied the internal relationship between urbanization, industrialization, EE, and ES and reported that industrialization and urbanization could promote ES by advancing EE. Improving EE is the most efficacious way to reduce energy consumption and pollutant emissions (Zhao et al., 2019). The International Energy Agency (2013) moved EE from the initial “hidden reserves” to the “number one source” in its “EE: Market Report 2013.” EE is crucial for sustainable energy development, and its evaluation and influencing factors have been gathering increasing attention. Based on the data envelopment analysis (DEA) and Malmquist productivity index,

* Corresponding author.
E-mail addresses: songmartin@126.com, songmartin@163.com (M. Song).

https://doi.org/10.1016/j.techfore.2022.122236
Received 19 May 2022; Received in revised form 8 October 2022; Accepted 24 November 2022
Available online 30 November 2022

Makridou et al. (2016) assessed the EE trend of five energy-intensive industries in 23 European Union countries between 2000 and 2009 and discussed its influencing factors. Liu et al. (2020) calculated China's regional EE from 2006 to 2016 using the DEA-BCC[1] model and applied the panel data model to study its impact factors.

Energy transition is imperative for the world to fight climate change (Karskens, 2016). This transition needs to restructure the energy system and integrate all participants by strengthening digitalization to make them more flexible (Gährs et al., 2021). The fusion of energy and digital revolution is a remarkable feature of energy innovation in the digital era. The innovation and development of digital technology have created infinite possibilities for the high-quality development of the energy industry (EI) (Sheveleva and Cherevik, 2022). The relationship between digital industry (DI) and EI has aroused researchers' interest; however, existing studies have mainly adopted qualitative analysis. Some scholars believe that the effect of the development of the digital industry (DDI) on EI has two sides (Loerincik, 2006). Zia (2016) pointed out that the manufacturing and use of information and communication technology (ICT) infrastructure and equipment directly increase energy consumption, while its application in other sectors can improve EE and reduce energy consumption.[2] A few scholars are concerned that DDI will adversely affect the sustained development of EI. Sadorsky (2012) used the dynamic panel demand model to explore the impact of ICT on power consumption in emerging economies and found that a significant positive relationship exists between ICT and power consumption. Sohail et al. (2014) ascertained that the rapid growth of the ICT sector has resulted in the growth in energy consumption and carbon emissions.

Researchers believe that DDI can advance the healthy development of EI by improving the allocation of energy resources and enhancing the efficiency of energy development and utilization (Bernstein and Madlener, 2010; Dabbous and Tarhini, 2021). Liu and Lu (2021) suggest that digital transformation in energy is efficacious in promoting energy allocation and optimizing energy scheduling. The application of digital technology can indirectly advance the exploitation of oil and gas resources and directly improve the production process. Based on data from 2008 to 2019, X. Zhang et al. (2022) examined the impact mechanism of industrial intelligence on energy intensity in China and found that the wide application of artificial intelligence could markedly decrease energy intensity through energy consumption reduction. In addition, the DDI can also foster an upgrade in the energy industry's structure, ensure the quality of energy resources, and reduce energy-related environmental pollution (Resniova, 2019; Tleuberdinova et al., 2020). Gährs et al. (2021) believed that ICT equipment, big data, machine learning, and the opportunities provided by their business models are vital steps toward a successful energy transformation, and digital technology will allow energy flows to be measured, controlled, and traded instantly. L. Wang et al. (2021) applied the KPWW[3] method and the multiple panel regression to analyze the effect of digital technology on carbon emission intensity. Their results show that digital technology will provide motive power for the country's green development. Increasing non-fossil energy use and improving the industrial structure through digital technology innovation are efficacious mechanisms to reduce carbon emission intensity.

The development evaluation of EI is the basis for national and regional policy-making; however, constructing the evaluation index system is incomplete. In addition, existing studies on its influencing factors do not examine the dynamic change process of EI development as a whole, nor do they fully consider the greater role of digital elements in the development of EI in the digital era. There is still a lack of studies on the integrated development of the digital and energy industries (DIEI). While researchers mostly discuss the impact of DI and its subdivided fields on energy consumption and EE, questions arise such as how to compute the fusion level of DIEI in a country or region? What is the quality of the integrated development of the two industries? What factors affect the integrated development of the two industries? These are not well answered; thus, it would be challenging for various economies to carry out a scientific plan for the high-quality development of the EI, which may make them miss many good opportunities and options for carbon emission reduction.

China is the largest country in energy production and consumption, with a relatively low development level of clean and low-carbon energy (Yang et al., 2020; Liu et al., 2021), and are the world's largest carbon emitter (M. Li et al., 2021). To cope with climate change and promote sustainable development, China proposed the "double carbon" goals in 2020: achieving carbon peaking by 2030 and carbon neutrality by 2060 (Han et al., 2022). The proposal of "double carbon" goals has injected a strong impetus into the international community's response to climate change. In addition, China's DI has achieved rapid development in recent years, providing more opportunities and choices for realizing its "double carbon" goals. The integrated development of DIEI is an important way for China to achieve its "double carbon" goals. Given the climate situation in China, it would serve as a good research sample with important policy implications for other countries. Consequently, China is the research object to study the issues mentioned above.

This study makes several novel contributions to the literature as follows: first, the mechanism of the integrated development of DIEI was explored. Second, based on the progressive law of industrial fusion development, the fusion level of DIEI[4] is measured from four aspects: fusion basis, fusion conditions, fusion application, and fusion performance. Third, the global principal component analysis (GPCA) method was applied to evaluate the fusion level of China's DIEI,[5] and its changes are analyzed from two aspects: time and space. Finally, the panel data model is applied to quantitatively study the factors affecting the integrated development of China's DIEI and examine each factor's influence direction and degree.

This study helps to accurately evaluate the fusion level of DIEI and correctly understand the integrated development status and its influencing factors on China's DIEI, which provides a reference for the Chinese government to advance the digitalization of EI and energy conservation of DI. The resulting improvements in the aforesaid areas in China can ultimately promote realizing its "double carbon" goals. Simultaneously, this study provides a new perspective for other countries or regions to better understand the development of China's EI and its carbon emission reduction.

The remainder of this paper is arranged as follows: Part 2 explores the fusion mechanism of DIEI; Part 3 builds the measurement index system for the fusion level of DIEI; Part 4 analyzes the spatial and

[1] BCC is the abbreviation for Banker, Charnes and Cooper (Banker et al., 1984).

[2] These effects are widely known as "IT as a problem" and "IT as a solution" or "green IT" and "IT for green," respectively. For detailed discussions, see Cai et al. (2013). The positive effects of ICT on energy consumption are also known as the rebound effect. For further discussion of the rebound effect, see Galvin (2015), Ahmed and Ozturk (2018), and Lange et al. (2020).

[3] KPWW is the abbreviation for Koopman, Powers, Wang and Wei (Koopman et al., 2010).

[4] Digital industry includes the communication equipment and computer manufacturing industry, electronic component manufacturing industry, other electronic equipment manufacturing industry, information transmission service industry, computer service, and software industry. The energy industry refers to the coal mining and washing industry, petroleum and natural gas mining industry, petroleum refining and nuclear fuel processing industry, coking industry, and power, heat, and gas production and supply industry.

[5] China's economic statistics and monitoring system is still carrying out statistics by industry, and is changing to the statistical monitoring system of the fusion of industries related to the digital economy. There is no direct statistical data on the fusion activities of DIEI (such as their added value). Therefore, this study indirectly measured the fusion level of DIEI.

temporal changes in the fusion level of DIEI in China; Part 5 examines the factors affecting fusion level of China's DIEI; Part 6 is a discussion of empirical results and follow-up research suggestions; finally, Part 7 summarizes the research findings and policy implications.

2. Analysis of the fusion mechanism of DIEI

The fusion of DIEI is a historical necessity for developing the two industries to a certain stage. Economic development, innovation, policy support, and social development are its main driving forces (as shown in Fig. 1). The process of DIEI from mutual penetration, separation, and differentiation to a new round of fusion is closely related to economic development. Economic development requires continual adjustment and optimization of the industrial structure; that is, the industrial structure is moving toward rationalization, high-grade, and greening. For example, to survive in the fierce competition or pursue high profits, digital and energy enterprises often continue to enhance the market competitiveness of enterprises and their products. The forward evolution of industrial structure promotes the gradual change of the development of DIEI from low-level to high-level and promotes the fusion of DIEI.

Innovation-driven is a new driving force for the development of industrial fusion, and its core contents are reflected in knowledge, technological, and institutional innovation (Wang, 2016). This involves knowledge and resources exchanged among many actors and their interrelationships in the business environment (Madanaguli et al., 2022). Innovation-driven is the bridge between DIEI and removes the obstacles to integrated development through reconfiguring digital, energy, knowledge, and human capital elements.

The integrated development of DIEI needs the strong support of government policies at the national level to make its economic development not lag behind other countries or occupy a place in international competition; each country will spare no effort to develop strategic industries such as DIEI and seize the development opportunity. In addition, the government often introduces a series of ER policies in the face of existing or possible serious environmental pollution. This will lead to and force cooperation and operation across industrial boundaries of digital and energy enterprises, and drive the integrated development of DIEI.

The development of DIEI is in the general social development environment, and a good social environment is conducive to the fusion of DIEI. In the social environment, urbanization is a necessary stage for the modernization development of countries or regions. It is conducive to the development of productive forces, the progress of science and technology, optimizing factor allocation, and upgrading industrial structure. It can create good conditions for the fusion of DIEI and has a strong pulling effect.

Driven by economic development, innovation, policy support, and social development, the mutual penetration of DIEI is deepening day by day, promoting the extension of their respective industrial chains, including the vertical and horizontal expansion of their industrial chains. In this process, the role of digital and energy elements has been effectively played. In other words, DI helps the digitalization of EI, EI provides high-quality energy safeguard for the development of DI, and related emerging industries are generated and developed. The fusion of DIEI is believed to exert far-reaching effects on the energy system, which in turn, may greatly improve carbon emission reduction (Wang et al., 2022). First, it promotes the potential excavation and benefits improvement of energy production (Barnewold and Lottermoser, 2020; Gährs et al., 2021). Second, it optimizes energy supply and reduces energy loss (Liu and Lu, 2021; Jaiswal and Thakre, 2022). Third, it advances energy conservation and efficiency, and decreases energy consumption intensity (Ren et al., 2021). Fourth, it improves energy structure and abates energy pollution (L. Wang et al., 2021).

3. Construction of the measurement index system for fusion level of DIEI

3.1. Design of the measurement index system

The integrated development of DIEI has its law—it is a gradual evolution and a progressive process. The construction of its evaluation index system should reflect the real level of the integrated development of DIEI, including the potential, direct performance, and achievements of the integrated development of the two industries. The potential of integrated development refers to the impact of the current development of DIEI on the integrated development of the two in the future; that is, the basic situation of fusion. It should also include the interdependence level between DI, EI, and various industries, reflecting the possibility of the fusion of DIEI; that is, the fusion conditions. The direct manifestation of the fusion of the two industries is the mutual penetration between DI and EI and the application and combination of their products in each other, called integrated application. In addition, the fusion performance of DIEI is the benefit produced by the fusion of the two. This benefit may be for the DI or EI or the broad external environment outside the two.

Therefore, the fusion level of DIEI can be measured from four aspects: fusion basis, fusion conditions, fusion application, and fusion performance. Among them, the fusion basis dimension mainly reflects

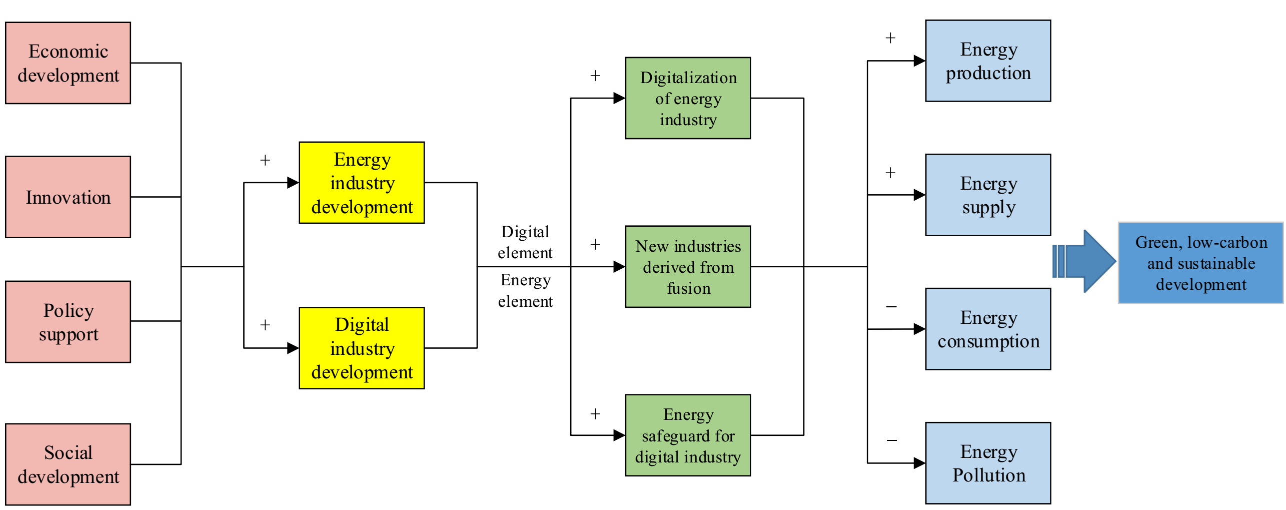

Fig. 1. The fusion mechanism of DIEI.
Source: Authors' visualization.

the current development level of the two integrated industries, including the development of DIEI. They amount to the "foundation" of the high-rise building, a "fusion of DIEI," where the foundation's stability determines the building's height. The dimension of fusion conditions mainly reflects the interrelationship between product input and demand of DI, EI, and various industries, including intermediate input, intermediate demand, push level and pull level. A good performance in these aspects will create a better environment for the growth and fusion of DIEI. The fusion application dimension reflects the coordination of the development level of DIEI and the matching of mutual demand of products, including the coordination level of output and the matching degree of input. Improving the output coordination level and input matching degree will promote the deepening and benign interaction between DI and EI. The fusion performance dimension reflects the achievements of the integrated development of DIEI, including factor utilization efficiency, energy product structure, and energy environmental protection level. The improvement of the factor utilization efficiency, optimization of energy product structure, and advancement of energy environmental protection level brought by the integrated development of the two industries will further promote the wider and deeper fusion of DIEI. Therefore, the construction of the measurement index system should start from the above dimensions.

3.2. The measurement index selection

According to the establishment thought of the measurement index system in the above section, considering the scientific and comprehensiveness of the index and the data availability and comparability, the selection of measurement indexes is as described below:

(1) Fusion basis indicators include DI and EI development indicators. Among them, the DI development indicators embody the length of long-distance optical cable lines per ten thousand square kilometers, the capacity of mobile telephone exchanges per ten thousand people, mobile phone penetration rate, telephone penetration rate (including mobile phones), the number of computers possessed by urban residents per 100 households, internet penetration rate, and added value of DI per capita, which represent the construction status of long-distance optical cable infrastructure, the infrastructure level of mobile telephone exchanges, the ownership of mobile phones, the telephone ownership, the number of computers owned, the degree of network application, and the development benefits of DI. The better the DDI, the more powerful the dynamic for the integrated development of DIEI; it will improve the breadth and depth of fusion and effectively promote their fusion process.

The EI development indicators embody the ratio of fixed asset investment in EI, the ratio of EI investment, the number of employees in electric power, thermal power, and gas production, and supply industry in urban units per 10,000 persons, the quantity of energy production per capita and added value of EI per capita, which stand for the investment status of fixed assets in EI, total investment level of EI, labor input in EI, production quantity of products in EI, and development benefits of EI. They jointly give expression to the development level of EI from different aspects. The more developed the EI, the stronger the foundation for the fusion of DIEI and the greater the market force to promote the fusion of the two.

(2) Fusion condition indicators include intermediate input and demand indicators and pull and push levels indicators. Among them, the intermediate input and demand indicators embody the intermediate input rate of DI, intermediate input rate of EI, intermediate demand rate of DI, and intermediate demand rate of EI, which represent the interconnection between DI and various industries in intermediate input, the interconnection between EI and various industries in intermediate input, the interconnection between DI and various industries in intermediate demand, and the interconnection between EI and various industries in intermediate demand.

The pull and push levels indicators embody the DI influence coefficient, EI influence coefficient, DI sensitivity coefficient, and EI sensitivity coefficient, which represent the driving effect of DI on other sectors, the driving effect of EI on other sectors, the sensitivity of DI to the development of other sectors, and the sensitivity of EI to the development of other sectors. The higher the respective intermediate input, intermediate demand, and pull and push levels of DIEI, the more capable they are to integrate with other industries, indicating that the better the conditions for the fusion of DIEI.

(3) Fusion application indicators include output coordination level and input matching level indicators. Among them, the output coordination level indicators embody the coupling degree between DI and EI and the coordination degree between DI and EI, representing the degree of interdependence between DI and EI and the coordinated development of DIEI. The input matching level indicators embody the fusion degree with EI as the main body, the fusion degree with DI as the main body, and the dual body fusion degree of DIEI, which represent the penetration degree of the EI into the DI, the penetration degree of the DI into the EI, and the comprehensive level of two-way penetration of the DIEI. The above indicators reflect the most direct performance of the current integrated development of DIEI.

(4) Fusion performance indicators include factor utilization efficiency, energy product structure, and energy environmental protection level indicators. Among them, the factor utilization efficiency indicators embody GDPs created by unit labor, unit capital, and unit energy consumption, which stand for the use efficiency of labor, capital, and energy factors.

The energy product structure indicators embody the ratio of natural gas, electricity, and other energy consumption; the ratio of natural gas, electricity, and other energy production; and the ratio of thermal power generation, which characterizes the clean energy consumption level, the clean energy production level, and the pollution degree of thermal power generation.

The energy environmental protection level indicators embody the SO_2 emissions for every unit of energy consumption, CO_2 emissions for every unit of energy consumption, wastewater and petroleum pollutant emissions for every unit of energy consumption, and discharge quantity of volatile phenol in wastewater per unit of energy consumption, which characterizes the SO_2 pollution from energy consumption, CO_2 pollution from energy consumption, wastewater oil pollution from energy consumption, and wastewater volatile phenol pollution from energy consumption. The fusion performance indicators reflect the benefits of the integrated development of DIEI (the smaller the pollution for every unit of energy consumption, the better), which is the goal of the integrated development of the two. Under the same conditions, the higher the fusion application level, the higher the fusion performance.

In conclusion, the study constructs an evaluation quota system for the fusion level of DIEI, which includes one target layer (fusion level of DIEI), four-dimension layers (fusion basis, fusion conditions, fusion application, and fusion performance), and nine measurement layers, with 35 indicators (see Table 1). Among them are 30 positive indicators and five negative indicators.

4. Measurement of the fusion level of China's DIEI

4.1. Research object and data description

To better grasp the fusion of China's DIEI, a comparison is made in

Table 1
Measurement index system of fusion level of DIEI.

Dimension	Metric	Indicator	Indicator unit	Indicator type	Indicator meaning
Fusion basis	DI development	Length of long-distance optical cable lines per ten thousand square kilometers	Kilometers/10,000 km^2	Positive	Y_1 = Length of long-distance optical cable lines / land area
		Capacity of mobile telephone exchanges per ten thousand people	Subscribers/10,000 persons	Positive	Y_2 = Capacity of mobile telephone exchanges / permanent population
		Telephone penetration rate (including mobile phone)	Subscribers/100 persons	Positive	Y_3 = Number of telephone subscribers / permanent population
		Mobile phone penetration rate	Subscribers/100 persons	Positive	Y_4 = Number of mobile phone subscribers / permanent population
		Number of computers possessed by urban residents per 100 households	Set/100 households	Positive	Y_5 = Number of computers owned by urban residents / number of urban households
		Internet penetration rate	%	Positive	Y_6 = Number of Internet users / permanent population
		Added value of DI per capita	Yuan/person	Positive	Y_7 = Added value of DI / permanent population
	EI development	Ratio of fixed asset investment in EI	%	Positive	Y_8 = Investment in fixed assets of EI in state-owned economy / total investment in fixed assets
		Ratio of EI investment	%	Positive	Y_9 = EI investment / GDP
		Number of employees in electric power, thermal power and gas production and supply industry in urban units per 10,000 persons	Person/10,000 persons	Positive	Y_{10} = Number of employees in electric power, thermal power and gas production and supply industry in urban units / permanent population
		Quantity of energy production per capita	Tons of standard coal equivalent/person	Positive	Y_{11} = Quantity of energy production / permanent population
		Added value of EI per capita	Yuan/person	Positive	Y_{12} = Added value of EI / permanent population
Fusion conditions	Intermediate input and demand	Intermediate input rate of DI	1	Positive	Y_{13} = Intermediate input of DI / total input of DI
		Intermediate input rate of EI	1	Positive	Y_{14} = Intermediate input of EI / total input of EI
		Intermediate demand rate of DI	1	Positive	Y_{15} = Intermediate use of DI / (Intermediate use of DI + final use of DI)
		Intermediate demand rate of EI	1	Positive	Y_{16} = Intermediate use of EI / (Intermediate use of EI + final use of EI)
	Pull and push levels	DI influence coefficient	1	Positive	Y_{17} = The increased production demand of other industries due to every additional unit of final product of DI
		EI influence coefficient	1	Positive	Y_{18} = The increased production demand of other industries due to every additional unit of final product of EI
		DI sensitivity coefficient	1	Positive	Y_{19} = Output produced and provided by DI for each additional unit of final use in each industry
		EI sensitivity coefficient	1	Positive	Y_{20} = Output produced and provided by EI for each additional unit of final use in each industry
Fusion application	Output coordination level	Coupling degree between the DI and the EI	1	Positive	Y_{21} = Degree of coupling between the DI and the EI, calculated by the static coupling model
		Coordination degree between the DI and the EI	1	Positive	Y_{22} = Degree of coordination between the DI and the EI, calculated by the static coupling model
	Input matching level	Fusion degree with EI as the main body	1	Positive	Y_{23} = (EI input rate in DI + demand rate of DI consumed by EI) / 2
		Fusion degree with DI as the main body	1	Positive	Y_{24} = (Demand rate of EI consumed by the digital energy + input rate of the DI to EI) / 2
		Dual body fusion degree of DIEI	1	Positive	Y_{25} = (Fusion degree with EI as the main body + Fusion degree with DI as the main body) / 2
Fusion performance	Factor utilization efficiency	GDP created by unit labor	Yuan/person	Positive	Y_{26} = GDP / number of employed persons
		GDP created by unit capital	1	Positive	Y_{27} = GDP / capital stock
		GDP created by unit energy consumption	Yuan/ton of standard coal equivalent	Positive	Y_{28} = GDP / total amount of energy consumption
	Energy product structure	Ratio of natural gas, electricity, and other energy production	%	Positive	Y_{29} = Quantity of natural gas, electricity, and other energy production / total amount of energy production
		Ratio of natural gas, electricity, and other energy consumption	%	Positive	Y_{30} = Quantity of natural gas, electricity, and other energy consumption / total amount of energy consumption
		Ratio of thermal power generation	%	Negative	Y_{31} = Scale of thermal power generation / total amount of power consumption
	Energy environmental protection level	SO_2 emissions for every unit of energy consumption	Tons/10,000 tons of standard coal equivalent	Negative	Y_{32} = SO_2 emissions / total amount of energy consumption
		CO_2 emissions for every unit of energy consumption	Tons/ton of standard coal equivalent	Negative	Y_{33} = CO_2 emissions / total amount of energy consumption
		Wastewater and petroleum pollutant emissions per unit energy consumption	Kilograms/10,000 tons of standard coal equivalent	Negative	Y_{34} = Wastewater and petroleum pollutant emissions / total amount of energy consumption
		Discharge quantity of volatile phenol in wastewater per unit energy consumption	Kilograms/10,000 tons of standard coal equivalent	Negative	Y_{35} = Discharge quantity of volatile phenol in wastewater / total amount of energy consumption

Note: In "EI development," "quantity of energy production" represents the quantity of primary energy production (Y_{11}); in "energy product structure," "electricity" represents the primary electricity, and "other energy" represents the energy sources other than natural gas, heat, electricity, coal, and petroleum products (Y_{29}–Y_{30}).

time and space. Owing to the availability of index data, 17 years from 2002 to 2018 were chosen as the study period at the national level. At the regional level, 30 provinces (autonomous regions, municipalities) in China except Tibet, Hong Kong, Macao, and Taiwan were selected as the study objects, and 2002, 2007, 2012, and 2017 were selected as the research time points.

The data were collected from China Environment Yearbook; China Labour Statistical Yearbook; China Energy Statistical Yearbook; China Statistical Yearbook on Environment; China Statistical Yearbook; Wangsu China Internet Development Report 2017; Statistical Yearbooks of various provinces of China; the websites of the State Council of China, National Bureau of Statistics of China, and China Electricity Council, GB/T 2589-2020 General Rules for Calculation of the Comprehensive Energy Consumption, Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (Trial), and 2006 IPCC Guidelines for National Greenhouse Gas Inventories, and sorted to obtain the corresponding data required for the study. The backward (or forward) interpolation method was used to supplement the missing individual data in the statistics.

To accurately measure the fusion level of DIEI, the value-based data used for overall merit were based on 2002, excluding the impact of price factors, such as GDPs created by unit labor, unit capital, and unit energy consumption; per capita DI added value; and per capita EI added value. Simultaneously, the data collected were standardized to remove the deviation generated by the attribute as much as possible. In light of the different properties of indicators, the positive and negative indicators were standardized by the following formula.

Positive indicators:

$$v_{ij} = \frac{d_{ij}\text{-}min\left(d_{ij}\right)}{max\left(d_{ij}\right)\text{-}min\left(d_{ij}\right)} \tag{1}$$

Negative indicators:

$$v_{ij} = \frac{max\left(d_{ij}\right)\text{-}d_{ij}}{max\left(d_{ij}\right)\text{-}min\left(d_{ij}\right)} \tag{2}$$

Here, d_{ij} is the original value of the j-th indicator of the i-th assessment objective; min(d_{ij}), max(d_{ij}) are respectively the minimum and maximum values of the j-th indicator in all assessment objectives; v_{ij} is the standardized value of the j-th indicator of the i-th assessment objective.

4.2. Research method and calculation

Principal component analysis (PCA) is a multivariate statistical method applying dimension reduction to transform many indices into a few. The determined weight is more reasonable and objective (Liu, 2022). However, this method is aimed at a plane data table composed of samples and indicators without adding time series.

The GPCA method is a combination of time series analysis and principal component analysis. Compared with the classical PCA method, it can analyze the dynamic changes of research objects over time (J. Wang et al., 2021). According to the correlation analysis of the evaluation indicators, the correlation between many indicators is strong, which means that their information expression overlaps, and the existing information must be concentrated.

Therefore, the GPCA method is used to make a tentative discussion and analysis in measuring the fusion level of DIEI. First, Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests were conducted, and the results are shown in Table 2. The coefficient of the KMO test is 0.791 (higher than 0.5), the χ^2 statistical value in Bartlett's sphericity test is 7293.702, and the P-value (adjoint probability) is 0.000 (lower than 0.05). It can be seen that it is suitable for the use of GPCA. Then, the eigenvalues of the global principal components and their contribution rate were calculated. Taking the initial eigenvalue greater than 1.00 as the standard, seven principal components were determined, and their

Table 2
KMO and Bartlett's tests.

KMO measure of sampling adequacy		0.791
Bartlett's test of sphericity	Approx. chi-square	7293.702
	Degrees of freedom	595
	Sig. (P)	0.000

Source: Authors' calculations.

cumulative contribution rate reached 77.875 %. In light of the principal component eigenvalue and component matrix, the weight coefficient of the principal component matrix was computed. According to the linear weighted summation formula, the overall score and each dimension score of the fusion level of DIEI at the national and regional levels were calculated.

4.3. Results analysis at the national level

As shown in Table 3, at the national level, the fusion level of China's DIEI continued to improve from 2002 to 2018. The data showed that the fusion level score of China's DIEI in 2002 was 0.01327, which has increased yearly since then. In 2018, the score reached 0.11918, approximately 8.98 times that of 2002, with an average increase rate of 14.71 % per year. This shows that the integrated development of China's DIEI has made extraordinary achievements since 2002. The EI provides the energy needed for the rapid development of the DI. Meanwhile, DDI has greatly promoted the high-quality development of China's EI.

In 2018, the scores of each dimension of the fusion of China's DIEI were ranked from high to low as follows: fusion basis, fusion performance, fusion conditions, and fusion application. In each dimension, like the comprehensive level, the score of the fusion basis dimension was always greater than 0 during the study period, increasing year by year and much higher than in other dimensions. It increased from 0.01563 in 2002 to 0.11880 in 2018. In terms of fusion basis, the development score of DI each year is much higher than that of EI. Compared with 2002, the scores of other dimensions increased in 2018, but the change in absolute value was relatively limited. The integrated development of DIEI is still at the stage of consolidating the fusion basis, continuously promoting fusion application, and improving fusion performance.

4.4. Results analysis at the regional level

4.4.1. Performance of each dimension

This study computed the respective scores of the four dimensions of China's regional DIEI fusion (fusion basis, fusion conditions, fusion application, and fusion performance) in 2002, 2007, 2012, and 2017. Their spatial distribution and changes are shown in Figs. 2 and 3.

The score of fusion basis dimension of China's regional DIEI generally showed an upward trend, which was mainly due to the rapid DDI. When comparing the Eastern, Central, and Western regions, the fusion basis score in the Eastern region was the highest. From 2002 to 2017, the fusion basis scores of the Western (West), Central (Middle), and Eastern (East) have continued to rise. Although there was still a certain gap (absolute gap) and an increase in the scores of fusion basis dimension between the Middle, West, and East in 2017, their relative gap has been greatly reduced compared with 2002. The role of western development strategy in the rapid growth of the West cannot be sidelined. The respective fusion basis level for all provinces except Fujian was increasing overall, and the ranking of each province was not stable. In 2017, there were four provinces with fusion basis scores greater than 0.15, namely Beijing, Shanghai, Tianjin, and Zhejiang. There were 6 provinces with fusion basis scores less than 0.10, with Yunnan being the lowest. There were great differences in the fusion basis level between different regions, owing to the scientific and technological (ST) level, economic development level, and industrial structure of each region.

The fusion condition scores of China's regional DIEI fluctuated

Table 3
Score of fusion levels of national DIEI.

Year	Dimension				
	Fusion basis	Fusion conditions	Fusion application	Fusion performance	Comprehensive level
2002	0.01563	−0.00203	−0.00049	0.00016	0.01327
2003	0.02184	0.00049	−0.00044	0.00015	0.02205
2004	0.02728	0.00074	−0.00043	0.00016	0.02775
2005	0.03306	−0.0009	−0.00038	0.00017	0.03195
2006	0.03898	−0.00148	−0.00042	0.00019	0.03726
2007	0.04854	0.00026	−0.00046	0.00021	0.04855
2008	0.05847	−0.00144	−0.00040	0.00024	0.05687
2009	0.06900	−0.00147	−0.00040	0.00026	0.06739
2010	0.07507	0.00027	−0.00041	0.00029	0.07522
2011	0.08501	−0.00123	−0.00040	0.00031	0.08369
2012	0.09259	0.00058	−0.00045	0.00034	0.09306
2013	0.09722	0.00025	−0.00033	0.00037	0.09751
2014	0.10108	0.00115	−0.00030	0.00041	0.10235
2015	0.10339	0.00223	−0.00028	0.00044	0.10577
2016	0.10515	0.00104	−0.00025	0.00048	0.10642
2017	0.11234	−0.00014	−0.00022	0.00051	0.11249
2018	0.11880	0.00003	−0.00020	0.00055	0.11918

Source: Authors' calculations.

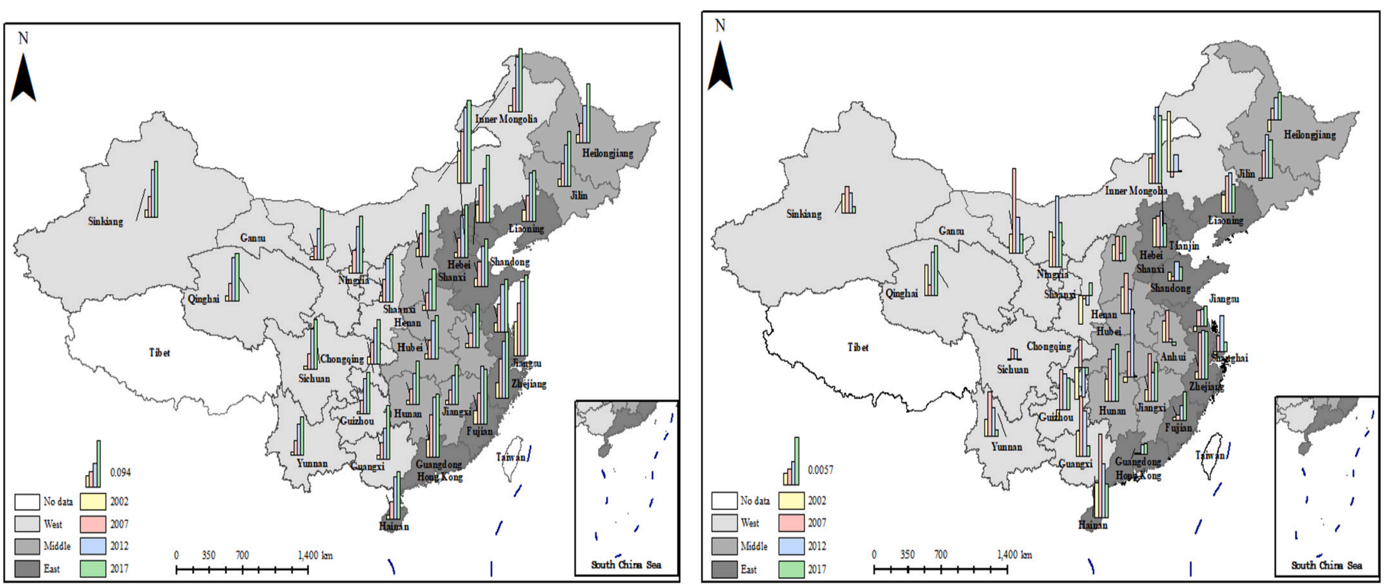

Fig. 2. Fusion basis (left) and fusion conditions (right) distribution of regional DIEI in 2002, 2007, 2012, and 2017 in China.
Source: Authors' calculations and visualization.

greatly during the study period. The fusion condition scores of DIEI in 2017 were ranked from high to low as follows: Eastern, Central, and Western regions. Their fusion condition scores have increased compared with 2002, but decreased by 0.00092, 0.00103, and 0.00113, respectively, compared with 2012, which was related to China's environmental regulation (ER) policy. With the rapid development of the economy and society, the state has been strengthening its ER. In the short term, the industrial structure was difficult to change rapidly and the fusion conditions have deteriorated. From the inter-provincial perspective, 22 provinces had higher scores of fusion conditions in 2017 than in 2002; the top six provinces with higher scores were Guizhou, Beijing, Shaanxi, Jilin, Zhejiang, and Heilongjiang. In addition, the fusion condition scores of eight provinces were lower than those in 2002; the three provinces with the greatest decline were Inner Mongolia, Henan, and Anhui. In 2017, the fusion condition scores of Beijing, Hunan, Qinghai, and Zhejiang were greater than 0.006, and that of the other 26 provinces were less than 0.006. It should be noted that Sichuan, Anhui, Chongqing, Tianjin, and other regions with rich energy resources or relatively developed economy ranked lower in terms of fusion condition scores.

During the research period, the score of fusion application in China's regional DIEI also fluctuated greatly. From the perspective of the three regions, the fusion application scores of the Eastern, Central, and Western regions increased first, and then decreased. In 2017, fusion application scores were ranked from high to low as follows: the Eastern, Central, and Western regions. Compared with 2002, the gap between the Central, Western, and Eastern regions was narrowing. At the inter-provincial level, five provinces had increasing fusion application scores, namely Guangdong, Jiangsu, Chongqing, Inner Mongolia, and Hunan. In 2017, Beijing scored the highest and Gansu scored the lowest in fusion application among all provinces. The fusion application level varied greatly in different provinces; the fusion application level of Gansu, Henan, Hainan, and Jilin was relatively low, owing to the low coordination degree between DI and EI, or fusion degree with DI as the main body.

With the increasing breadth and depth of the fusion in China's DIEI, the overall fusion performance level has also improved. As the world's second largest economy, China's energy consumption is huge. The improvement of the fusion performance of its DIEI is also benefiting the

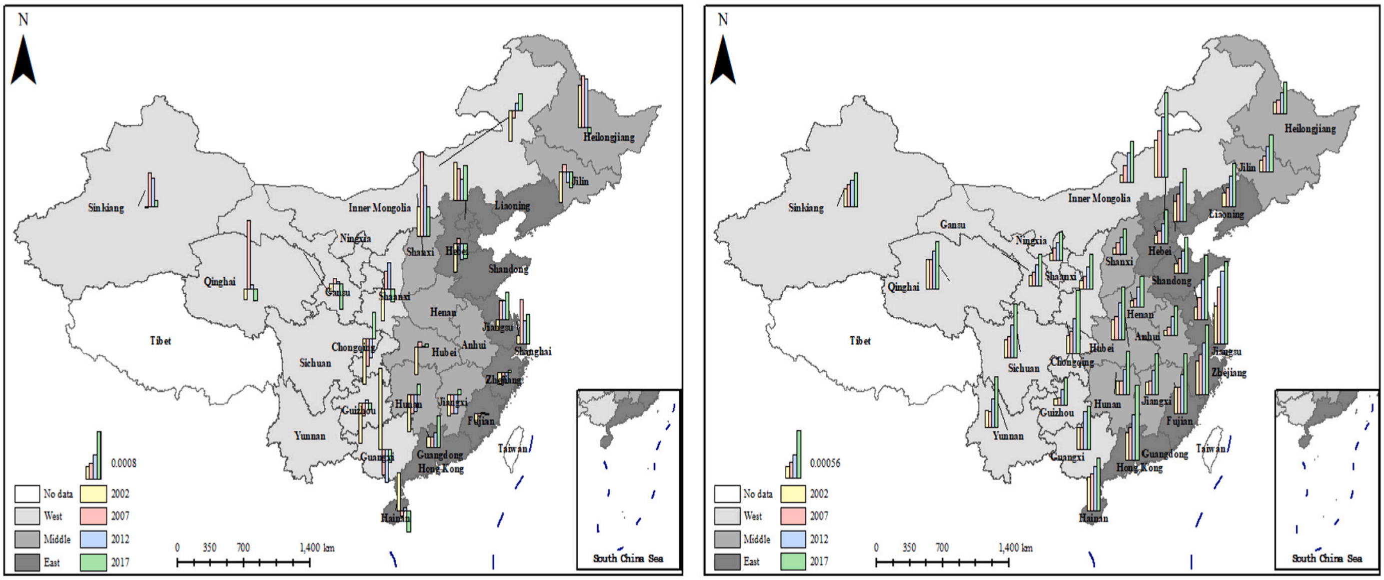

Fig. 3. Fusion application (left) and fusion performance (right) distribution of regional DIEI in 2002, 2007, 2012, and 2017 in China.
Source: Authors' calculations and visualization.

world. Compared with 2002, the fusion performance of China's regional DIEI in 2017 has greatly improved. During the study period, the fusion performance level of the Eastern, Central, and Western regions had continuously improved. The fusion performance scores were ranked from high to low as follows: the Eastern, Western, and Central regions. In terms of provinces, in addition to Guangxi, Yunnan, and Hunan, the fusion performance level of the other 27 provinces had also continuously improved. Among them, the four provinces with the largest increase in fusion performance scores were Jiangsu, Beijing, Guangdong, and Chongqing; the four provinces with the least increase were Sinkiang, Qinghai, Shanxi, and Hainan. In the context of environmental pollution, the improvement of the fusion performance of DIEI created a breakthrough for sustainable development, but the fusion performance level in different provinces was still significantly different. In 2017, the provinces with the highest and lowest fusion performance scores were Beijing and Shanxi respectively, and the gap between them expanded from 0.00041 in 2002 to 0.00078 in 2017. As a major coal province, Shanxi still has a long way to go in its green transformation.

4.4.2. Overall situation

Whether it be the Eastern, Central, and Western regions of China, or in provinces other than Fujian, the comprehensive score of the fusion level of DIEI showed an upward trend from 2002 to 2017, indicating that the development interaction between the two industries has been improving. Compared with 2012, Fujian's comprehensive level score of DIEI fusion decreased in 2017 owing to the changes in mobile phone infrastructure, telephone and computer ownership, EI investment and labor input, intermediate input and demand of EI, intermediate demand and promotion level of DI, input matching between the DI and the EI, CO_2 emission and so on. Contrarily, the comprehensive fusion level of China's regional DIEI depends on the strength of fusion basis, which implies that the deepening of the fusion application of DIEI and improvement of fusion performance need to be vigorously promoted.

During the study period, the Eastern region scored the highest in the comprehensive fusion level of DIEI. The absolute gap between the Central, Western, and Eastern regions in this regard widened, and the disparity between the provinces with the highest and lowest comprehensive fusion level was even greater. In 2017, the comprehensive fusion level scores of The East, Middle, and West was 0.14151, 0.11099, and 0.11684, respectively, an increase of 0.10546, 0.09658, and 0.10357, respectively, over 2002. From the perspective of provinces, Beijing, Shanghai, Zhejiang, Tianjin, Guangdong, and other regions with a better-developed economy ranked high in the comprehensive fusion level, while Guizhou, Yunnan, Anhui, Jiangxi, and other provinces with relatively backward economic development ranked low. Among them, the comprehensive fusion level score of Beijing in 2017 was 0.10863 higher than that of Yunnan (see Table 4). In summary, the integrated development of China's regional DIEI is still in a growth stage, while the

Table 4
Comprehensive fusion level score of regional DIEI.

Region	Year			
	2002	2007	2012	2017
Beijing	0.07787	0.12347	0.18219	0.19924
Tianjin	0.03511	0.08158	0.12040	0.15121
Hebei	0.01533	0.04933	0.10151	0.12147
Liaoning	0.02824	0.06199	0.11462	0.11927
Shanghai	0.07802	0.12357	0.17489	0.18765
Jiangsu	0.02120	0.06666	0.11091	0.12372
Zhejiang	0.03632	0.09590	0.13671	0.15784
Fujian	0.02947	0.07181	0.13245	0.12858
Shandong	0.01796	0.05658	0.09252	0.10936
Guangdong	0.04018	0.09664	0.13737	0.14491
Hainan	0.01682	0.05201	0.10469	0.11333
Eastern average	0.03605	0.07996	0.12802	0.14151
Shanxi	0.02065	0.05659	0.10174	0.12208
Jilin	0.01676	0.0566	0.10093	0.13097
Heilongjiang	0.01970	0.04867	0.09062	0.13930
Anhui	0.01172	0.03697	0.08012	0.09741
Jiangxi	0.01086	0.04078	0.06945	0.09526
Henan	0.01339	0.04397	0.07334	0.0937
Hubei	0.01038	0.04759	0.09728	0.10027
Hunan	0.01183	0.04047	0.07848	0.10892
Central average	0.01441	0.04646	0.08650	0.11099
Inner Mongolia	0.02033	0.05287	0.12762	0.14322
Guangxi	0.01426	0.04516	0.07623	0.12417
Chongqing	0.01274	0.05308	0.07808	0.10057
Sichuan	0.00754	0.03667	0.09231	0.11344
Guizhou	0.00278	0.03718	0.08607	0.09967
Yunnan	0.00990	0.03900	0.07550	0.09061
Shaanxi	0.00940	0.05089	0.09726	0.11061
Gansu	0.01065	0.04251	0.07649	0.11992
Qinghai	0.01673	0.04360	0.10584	0.11700
Ningxia	0.02244	0.05595	0.11708	0.13696
Sinkiang	0.01924	0.05084	0.11097	0.12906
Western average	0.01327	0.04616	0.09486	0.11684

Source: Authors' calculations.

integrated development of the two industries between regions is unbalanced and has great development potential.

5. Empirical analysis of the factors affecting the fusion of China's DIEI

5.1. Description of variables and data

Factors affecting the fusion level of DIEI may have different effects. First, the influencing factors of the integrated development of DIEI initially came from itself; that is, the development of DIEI. Their talent introduction, infrastructure construction, research and experimental development (R&D) investment, and industrial benefits strongly influence their respective development and determine the breadth and depth of their fusion. Only after the development of DIEI reaches a certain degree will their integrated development move forward to a higher level. When the two are within the scope of good coordination and interaction development, their integrated development can move forward to more sustainable development.

Advanced ST level helps improve the fusion level of DIEI, and ST innovation is a perpetual impetus to advance its sustained development. ST innovation can break the original development dilemma, promote the popularization, and application of new technologies such as big data, promote the reform of EI, optimize energy structure (J. Li et al., 2021), and advance the integrated development of DIEI.

Technological changes in the energy sector are largely caused by market environment and expectations and environmental policies such as carbon dioxide emission reduction rather than spontaneity (Grubb et al., 2002; Bretschger, 2005). Reasonable ER policies can help the transformation and upgradation of EI and create fairly favorable conditions for the integrated development of DIEI. For example, such policies can enhance EE and reduce pollutant emissions by promoting technological innovation and application (Porter and Van der Linde, 1995). Timchenko et al. (2019) believed that sustainable development policies to promote low carbonization, energy infrastructure utilization, or EE, can drive energy digitization.

Industrial structure is the composition between different industrial sectors of the national economy and within them. It reflects the relationship between different production factors within industries or different industries in time, space, and level. The increase in the industrial structure level implies that the industrial structure is moving toward rationalization or high class. The former refers to the coordination between industries realized under the current technical conditions, and the latter follows the historical and logical law of economic development from low to high levels. This will make the coordination and interaction closer within various industries or between different industries, drive DDI, promote the innovation of EI, deepen and optimize the link and complementary relationship between them, and form a good trend of integrated development of DIEI.

Urbanization can also impact the fusion level of DIEI. High-quality urbanization can make better use of urban infrastructure, human resources, and energy resources through the guidance of reasonable distribution of urban population and scientific division of labor within and among industries, thereby promoting the R&D, popularization, and application process of digital technology and the economical, intensive, and clean utilization of energy. An increase in population density is likely to bring about the effect of population agglomeration and industrial clusters and facilitate the integrated development of DIEI.

Therefore, this study selected the DI development level (*dig*), EI development level (*ene*), ST innovation level (*tec*), industrial structure level (*ind*), ER level (*env*), and urbanization level (*urb*) as the research variables, which were expressed in terms of per capita DI added value, per capita EI added value, domestic patent application authorization per 10,000 people, the ratio of the added value of the secondary and tertiary industries to GDP, the ratio of industrial pollution control investment to GDP, and the ratio of urban population to the total population, and explored their impact on the fusion level of DIEI (*edt*).

The 30 provinces in the previous section were chosen as the study object, and 2002, 2007, 2012, and 2017 were selected as the time observation points. The integrated level score of DIEI calculated above was applied to compute the fusion level of DIEI. Other research data were extracted from the corresponding China Statistical Yearbooks on Science and Technology, China Statistical Yearbooks, China Environment Yearbooks in 2002, 2007, 2012, and 2017, and the website of the National Bureau of Statistics of China. To measure variables more accurately, the value-based data were taken as the base period in 2002, and the influence of price factors was excluded, such as the per capita DI added value and per capita EI added value. Meanwhile, the chosen variables were logarithmically processed to eliminate the multicollinearity and heteroscedasticity between variables (see Table 5).

5.2. Construction of panel data model

5.2.1. Unit root test and cointegration test

The panel data model was utilized to analyze the influence factors of the fusion of China's DIEI. To prevent pseudo regression and guarantee the accuracy of estimation results, Fisher-type stationarity tests and Levin-Lin-Chu (LLC) stationarity tests were done for each variable. The corresponding results of the unit root test are shown in Table 6, in which PP-FCS, ADF-FCS, and LLC-T refer to the Fisher-PP, Fisher-ADF tests statistics, and LLC test statistics, respectively.

These six variables except *lntec* reject the null hypothesis with a significance level of 1 %, revealing that these six variables have no unit roots and are stationary sequences. However, since the unit root test for *lntec* cannot reject the hypothesis that "there is no unit root." Therefore, to further determine whether the panel data model can be constructed, performing a cointegration test for dependent and independent variables is imperative. The Kao cointegration test method is used here, and the test results are shown in Table 7. The results show that the original assumption that "no cointegration relationship exists between the variable" is rejected at the 1 % significance level; that is, a cointegration relationship exists between the above variables, which can further help construct the panel data model.

5.2.2. Granger causality test

To avoid pseudo regression, the Granger causality test method was further applied to determine whether the independent variables Granger caused the dependent variable. The results of the test are shown in Table 8. The impact of ER on the integration of DIEI is often lagging and long-term (Porter, 1991; Zhang et al., 2020). Affected by the limited years of available data, it failed to prove that *lnenv* is the Granger cause of *lnedt*, but this does not mean that *lnenv* is not the Granger cause of *lnedt*. In addition, the results show that other independent variables rejected the null hypothesis at least at the 10 % significance level; that is, *lndig*, *lnene*, *lntec*, *lnind*, and *lnurb* are the Granger causes of *lnedt*.

5.2.3. Model estimation

To reflect the relationship between variables more precisely, it is necessary to clarify the type of panel data model to be established. In other words, whether it is a mixed effect model should be judged first. If it is not a mixed effect model, it needs to be clarified whether it belongs to a random or fixed effect model. The model was set as follows:

$$lnedt_{it} = \alpha_i + lndig_{it}\phi_i + lnene_{it}\sigma_i + lntec_{it}\lambda_i + lnind_{it}\theta_i + lnenv_{it}\eta_i + lnurb_{it}\omega_i + \varepsilon_{it} \tag{3}$$

Here, $lnedt_{it}$, $lndig_{it}$, $lnene_{it}$, $lntec_{it}$, $lnind_{it}$, $lnenv_{it}$, $lnurb_{it}$ represent the fusion level of DIEI, DI development level, EI development level, ST innovation level, industrial structure level, ER level, and urbanization level. ϕ_i, σ_i, λ_i, θ_i, η_i, $\omega_i$are the respective coefficients of the last six independent variables; α_i represents the constant term of the model and ε_{it} represents random error term. $i = 1, 2, \cdots, 30$; $t = 1, 2, 3, 4$.

Table 5
Variables' descriptive statistics.

Descriptive statistics	*lnedt*	*lndig*	*lnene*	*lntec*	*lnind*	*lnenv*	*lnurb*
Mean	−2.83300	6.51679	7.22903	0.73754	4.47564	0.13744	3.89105
Median	−2.55040	6.33325	7.25195	0.77470	4.48540	0.17805	3.89740
Maximum	−1.61320	9.14340	9.21330	3.88670	4.60180	2.04120	4.51700
Minimum	−5.88530	4.20680	4.83450	−1.83260	4.17950	−1.83260	3.19010
Std. Dev.	0.86065	1.12120	0.86930	1.42619	0.07482	0.79832	0.29701
Cross sections	30	30	30	30	30	30	30
Observations	120	120	120	120	120	120	120

Source: Authors' calculations.

Table 6
The results of unit root test.

Variable name	PP-FCS	ADF-FCS	LLC-T	Conclusion
lnedt	396.053***	299.799***	−47.5477***	Stationary
lndig	150.682***	109.654***	−124.957***	Stationary
lnene	188.657***	115.997***	−36.5769***	Stationary
lntec	38.9400	21.2274	−505.484***	Nonstationary
lnind	204.147***	142.314***	−94.0066***	Stationary
lnenv	130.083***	115.985***	−5.88703***	Stationary
lnurb	178.867***	128.179***	−36.6184***	Stationary

Source: Authors' calculations.
*** Indicates significance under the 1 % confidence level.

Table 7
Kao cointegration test results.

Kao cointegration test	Statistical value	
ADF	t-Statistic −9.38260	P-value 0.0000
Residual variance	0.09216	
HAC variance	0.09452	

Source: Authors' calculations.

Table 8
Granger causality test.

Null hypothesis	*F* statistics	*P*-value	Conclusion
lndig does not Granger cause *lnedt*	8.50632***	0.0006	Reject
lnene does not Granger cause *lnedt*	2.91615*	0.0626	Reject
lntec does not Granger cause *lnedt*	7.29860***	0.0015	Reject
lnind does not Granger cause *lnedt*	5.39255**	0.0226	Reject
lnenv does not Granger cause *lnedt*	0.86096	0.4753	Fail to reject
lnurb does not Granger cause *lnedt*	12.7030***	0.0000	Reject

Note: *, ** and *** indicate significance at the 10 %, 5 %, and 1 % confidence levels, respectively.
Source: Authors' calculations.

Then, the type of panel data model was judged by F-test and Likelihood Ratio (LR) test. The statistical values of the F-test and LR test were 6.32135 and 138.91514, respectively, and both *P*-values were 0.0000, less than 0.01. The original hypothesis had to be rejected at the 1 % level, revealing that it is not a mixed effect model. Subsequently, the Hausman test was conducted to judge whether it is a random or fixed effect model. The statistical value obtained from this test was 117.63247, and the P-value was 0.0000. The original hypothesis was also rejected at the 1 % level, proving that the fixed effect model should be used.

The estimated results that stem from the fixed effect model are shown in Table 9. Models 1, 2, and 3 in Model group A are panel data models with region fixed effect, time fixed effect, and region and time fixed effect, respectively. Model 1 is the best among the three models, with higher R^2 and variable significance. The value of R^2 statistic in Model 1 was 0.98119, the value of adjusted R^2 statistic was 0.97335, and the DW statistic was close to 2, indicating that this model has a good fitting effect. The *P*-values of variables *lnene*, *lntec*, and *lnurb* were less than 0.01, indicating that these variables were statistically significant at the 1 % level. In addition, the P-values of variables *lndig* and *lnenv* were less than 0.05, indicating that they were statistically significant at the 5 % level. However, the P-value of variable *lnind* was much greater than 0.10, indicating that it was not statistically significant.

To further study the impact of the industrial structure level, this study added the quadratic term *lnind***lnind* as a variable. Similarly, the panel data model estimation results, including the quadratic term, were obtained, as shown in Table 9 (Model group B). Similarly, Models 4, 5, and 6 in Model group B are models with region fixed effect, time fixed effect, and region and time fixed effect, respectively. Model 4 is the best among these three models, with higher R^2 and variable significance. The value of R^2 statistic in Model 4 was 0.98225, and the value of adjusted R^2 statistic was 0.97455, both were higher than that in Model 1. Durbin-Watson (DW) statistic was also close to 2, meaning there was no autocorrelation in the residual sequence. The *P*-values of variables *lnene*, *lntec*, *lnenv*, and *lnurb* were less than 0.01, indicating that they were statistically significant at the 1 % level. The P-values of variables *lnind***lnind* were less than 0.05, indicating that they were statistically significant at the 5 % level; The P-value of variable *lndig* was less than 0.1, indicating that it was statistically significant at the 10 % level. Except for variable *lnind*, the variable coefficients of Models 1 and 4 were positive, and most had little difference. In conclusion, the constructed model is reasonable, and Model 4 has a better fitting effect.

5.3. Analysis of empirical results

It is evident from Model 4 in Table 9 that the coefficients of DI development level, EI development level, ST innovation level, industrial structure level, ER level, and urbanization level were positively related to the dependent variables; that is, they produced a positive effect on advancing the integrated development of DIEI.

Among them, the variable coefficient of the development level of DI was 0.15704, which indicated that the fusion level of DIEI will change by 0.15704 percentage points for every 1 % increase in DI development level. The variable coefficient of the EI development level was 0.51715, which indicated that the fusion level of the two industries will increase by 0.51715 percentage points for every 1 % increase in the EI development level. During the research period, the development of EI produced a greater effect on the integrated development of DIEI, and its coefficient was 3.29 times of the development level of DI. Thus, DI still has a great potential.

The coefficient of ST innovation level was 0.13391. That is, for every 1 % increase in the ST innovation level, the fusion level of DIEI will increase by 0.13391 percentage points. As for the level of industrial structure, the primary term coefficient of this variable was negative and the secondary term coefficient was positive, which was significant at a 5 % level, indicating that the fusion level of DIEI had a significant nonlinear relationship with it. This was because the initial advancement of the industrial structure level was mainly due to the respective growth of the output scale of the secondary and tertiary industries. With the continuous increase of the output scale, the industrial boundary is gradually blurred and the fusion and penetration between different

Table 9
Estimation results of the panel data model for the fusion of China's DIEI.

Variable name	Model group A			Model group B		
	Coefficient (Model 1)	Coefficient (Model 2)	Coefficient (Model 3)	Coefficient (Model 4)	Coefficient (Model 5)	Coefficient (Model 6)
C	−15.24716***	−7.19597***	−13.93968***	146.73520*	40.56444	−170.67640*
	(3.66880)	(1.78220)	(3.78526)	(76.93487)	(56.67178)	(93.35675)
lndig	0.21630**	0.06030	0.05110	0.15704*	0.04879	0.09351
	(0.08501)	(0.04950)	(0.09953)	(0.08797)	(0.05136)	(0.10162)
lnene	0.50060***	0.02218	0.10675	0.51715***	0.02288	0.06200
	(0.03818)	(0.03236)	(0.08021)	(0.03808)	(0.03247)	(0.08367)
lntec	0.14181***	0.01257	0.03649	0.13391***	0.01328	0.05589
	(0.04322)	(0.03718)	(0.07865)	(0.04247)	(0.03726)	(0.07863)
lnind	0.53216	0.14779	0.80548	−73.64293**	−21.34473	72.33650*
	(0.89569)	(0.40226)	(0.94343)	(35.22173)	(25.49596)	(42.58184)
lnenv	0.05837**	0.04306	0.00148	0.07869***	0.04313	−0.01341
	(0.02808)	(0.03015)	(0.04180)	(0.02919)	(0.03022)	(0.04228)
lnurb	1.25707***	0.80519***	1.63703***	1.31628***	0.77246***	1.66008***
	(0.25002)	(0.15804)	(0.35121)	(0.24592)	(0.16372)	(0.34759)
*lnind**lnind*	–	–	–	8.48623**	2.42698	−8.15821*
				(4.03084)	(2.87926)	(4.85535)
R^2	0.98119	0.92231	0.96509	0.98225	0.92282	0.96628
Adjusted R^2	0.97335	0.91595	0.94871	0.97455	0.91574	0.94984
F statistics	125.17870	145.09450	58.92242	127.5866	130.32420	58.77627
P-value (F statistics)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DW statistics	2.25324	0.87617	1.93564	2.275649	0.88302	1.99439

Note: *, **, *** indicate significance under the 10 %, 5 %, and 1 % confidence levels, respectively. The values in the brackets of the columns are standard errors.
Source: Authors' calculations.

industries are getting closer and closer. The synergy effect accompanied by the industrial structure upgradation is increasing, thus promoting the integrated development of DIEI.

The coefficient of ER level was 0.07869, which implies that for every 1 % increase in ER level, the fusion level of DIEI will increase by 0.07869 percentage points. Compared with other variables, its value was the smallest, indicating that ER had the least effect on the integrated development of DIEI during the study period, but it was still conducive to the integrated development of the two industries. The coefficient of urbanization level was larger among the variables, reaching 1.31628, which was much higher than the influence of the DI development level, EI development level, ST innovation level, and ER level. The higher the urbanization level, the better the factors can be diversified and abundant for regional innovation and development to promote the advancement of innovation ability of various industries, and to create more favorable conditions for the integrated development of DIEI.

5.4. Robustness test

To further verify the relationship between the dependent and independent variables and the reliability of the model (Model 4), this study further conducted robustness tests in the following two ways.

First, the robustness of the model was investigated by measuring some variables with other indicators, and the robustness test results are

Table 10
Robustness test of the panel data model for the fusion of China's DIEI.

Variable name	Model group C			Model group D		
	Coefficient (Model 7)	Coefficient (Model 8)	Coefficient (Model 9)	Coefficient (Model 10)	Coefficient (Model 11)	Coefficient (Model 12)
C	131.22360**	148.11140**	29.48807	129.38350	266.00620***	272.34250***
	(61.90365)	(66.79746)	(90.27973)	(93.40007)	(81.15339)	(79.71052)
lndig	0.23747***	0.27417***	0.21669**	0.20183*	0.03370	0.14502
	(0.06828)	(0.07270)	(0.08501)	(0.11931)	(0.08250)	(0.10880)
lnene	0.52591***	0.55271***	0.44920***	0.46507***	0.53123***	0.59021***
	(0.02757)	(0.03737)	(0.05500)	(0.07415)	(0.04918)	(0.04740)
lntec	0.10995**	0.05010	0.10217**	0.16238***	0.13631***	0.08961
	(0.05382)	(0.06780)	(0.03969)	(0.06031)	(0.04442)	(0.05361)
lnind	−66.64504**	−75.04915**	−21.69134	−65.71516	−129.47590***	−131.67200***
	(28.36392)	(30.70746)	(41.25022)	(42.86581)	(37.51301)	(37.47188)
lnenv	0.03780	0.03707	0.00732	0.05151	0.11352***	0.09334***
	(0.02577)	(0.02908)	(0.02362)	(0.03284)	(0.03062)	(0.02981)
lnurb	1.69421***	1.51501***	1.70056***	0.94397***	1.38863***	1.13145***
	(0.22225)	(0.26540)	(0.36927)	(0.34326)	(0.27500)	(0.38652)
*lnind**lnind*	7.58592**	8.64146**	2.64955	7.66059	15.02238***	15.17406***
	(3.24393)	(3.53132)	(4.73020)	(4.92583)	(4.33925)	(4.43033)
R^2	0.99405	0.98242	0.97664	0.97061	0.98188	0.99139
Adjusted R^2	0.99147	0.97479	0.96651	0.95705	0.97328	0.98576
F statistics	385.25000	128.81260	96.38178	71.55376	114.19750	176.07100
P-value (F statistics)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DW statistics	2.22888	1.90955	2.14351	2.34386	2.57040	2.45634

Note: *, **, *** indicate significance under the 10 %, 5 %, and 1 % confidence levels, respectively. The values in the brackets of the columns are standard errors.
Source: Authors' calculations.

shown in Model group C of Table 10. Models 7 and 8 in Model group C differ from Model 4 in the measurement of the variable of *tec*. In Model 7, the full-time equivalent of R&D personnel per 10,000 persons (man-year/10,000 persons) was used to measure the ST innovation level, whereas the indicator of "ratio of expenditure on R&D to GDP" (%) was adopted in Model 8 to measure this variable. Model 9 in Model group C differs from Model 4 in the measurement of the variable of *urb*; for the former, *urb* was measured by the ratio of number of employed persons in the secondary and tertiary industries to all employed persons. The models selected for the robustness test are consistent with Model 4, namely, the panel data model with region fixed effect. Results show that R^2 of Models 7, 8, and 9 are greater than 0.96, the coefficient symbols of each independent variable are consistent with Model 4, and the coefficients of most independent variables are significant at least at the 5 % significance level.

Subsequently, the robustness of the model was examined by reducing the number of samples and modeling different regions, and the robustness test results are shown in Model group D of Table 10. Models 10, 11, and 12 in Model group D differ from Model 4 in the number and scope of regions. These three models are also the panel data model with region fixed effects. The research objects of Model 10 include the Eastern, Central, and Western regions except Beijing, Tianjin, Hebei, Qinghai, Ningxia, and Sinkiang, which are the first three provinces and last three provinces in Table 4. The research objects of Model 11 include the Eastern and Western regions. Model 12 includes the Eastern regions. Similarly, R^2 of Models 10, 11, and 12 are close to 1, the coefficient symbols of each independent variable are the same as Model 4, and the coefficients of most independent variables are statistically significant. In conclusion, the regression results of Models 7–12 are generally consistent with Model 4, which suggests that those of Model 4 are robust.

6. Discussion

In the face of environmental problems such as climate change, many countries have taken various measures to reduce carbon emissions. China has also made great efforts to achieve its "double carbon" goals. Among them, the digital economy is paving the way for improving carbon emission performance (W. Zhang et al., 2022). Digital technology has many advantages, and its role in the development of EI should not be ignored. Its development can also promote green innovation, which helps induce green total factor productivity (Zhao et al., 2022b). To meet the challenges of oil prices dropping or increasingly complex government regulations, energy enterprises are seeking digital transformation (Baird, 2016). The digital revolution and Internet of Things have stimulated the development of product/service systems to be more integrated (Struckell et al., 2021).

It is of great significance to study the integrated development of DIEI. Among them, the fusion level of DIEI is one of the important contents. Most of the previous studies in this area only used a single indicator or a few indicators to describe the situation at a certain dimension, which did not reflect their fusion level well. This study established a comprehensive evaluation index system for the fusion level of DIEI, including four dimensions: fusion basis, fusion conditions, fusion application, and fusion performance. The construction of this evaluation index system followed the rule of gradual evolution and progressive process for the fusion of DIEI, reflecting the potential, direct performance, and achievements of the integrated development of DIEI, and measured the actual level of their fusion correctly. Based on the evaluation index system, this study used the GPCA method to measure the fusion level of China's DIEI from 2002 to 2018. Empirical results suggested that the fusion level of China's DIEI was rising during the research period, but it needs to be further improved.

Additionally, the factors affecting the fusion of DIEI are another important content area. The existing research on the influencing factors of the fusion of DIEI is mainly qualitative analysis (Ammer, 2017; Midttun and Piccini, 2017), while quantitative research is rare. Based on the qualitative analysis of the fusion mechanism of DIEI, this study applied the panel data model to quantitatively study its impact factors. The results showed that in the process of their fusion, the enhancement factors in order of effects from large to small were urbanization, EI development, DI development, ST innovation, and ER levels. This relationship between the fusion level of DIEI and the ST innovation level is in line with Paramati et al. (2022). In addition, there was a significant U-shaped relationship between the fusion level of DIEI and the industrial structure level. This result enriches the study of the fusion of DIEI and is conducive to follow-up research.

Promoting "double carbon" goals is a systematic project, and there are still many issues to be solved, including theory and practice. Due to the limitation of research data availability, quantitative studies in related fields have been affected to a certain extent, and subsequent breakthroughs can be sought in this regard. Although this study analyzed the fusion mechanism of DIEI, it does not quantitatively explore the specific impact of the integrated development of DIEI on "double carbon" goals and its mechanism. Future studies should consider the dynamic impact of the integrated development of DIEI on promoting the realization of China's "double carbon" goals, predict the extent to which the "double carbon" goals can be achieved in the next few years, and explore the level that the integrated development of DIEI would have to reach at least when the "double carbon" goals were achieved. Additionally, the results of this study were based on the relevant data on DIEI fusion from the perspective of a developing country (China); this limits the generalization of our research results to only countries with similar features. Future research could investigate the situation in this regard from different countries, including developing and developed countries, and conduct comparative analysis.

7. Conclusions and implications

Although China's environmental protection measures have been strengthened, environmental pollution problems persist. Using ST, especially digital technology, is crucial to advance sustainable development in EI. The rapid growth of DI also needs continuous support from EI. Therefore, it is only wise that China advances its sustainable development through the integrated development of DIEI, and the study on this aspect needs further improvement.

This study builds a measurement index system of the fusion level of DIEI from four dimensions: fusion basis, fusion conditions, fusion application, and fusion performance. Taking China as the research object, the GPCA method was applied to compute the fusion level of DIEI at the national and regional levels. On this basis, the panel data model was utilized to quantitatively study the impact factors of the integrated development of China's DIEI. This study researched the development of two important fields (DIEI) in the same framework, and comprehensively measured their fusion level, which is rarely done in the existing literature. The measurement index system for fusion level of DIEI covered four dimensions: fusion basis, fusion conditions, fusion application, and fusion performance, improving the existing evaluation research of them. The fusion mechanism analysis of DIEI revealed their internal relationship, laying a foundation for the quantitative study of their interaction relationship and fusion effect. Additionally, empirical analysis of the factors affecting the fusion of China's DIEI serves to enrich the research on their influencing factors.

Several important conclusions are drawn from the study. First, at the national level, the fusion level of China's DIEI continued to improve from 2002 to 2018. Regarding each dimension, the scores in 2018 were ranked from high to low as follows: fusion basis, fusion performance, fusion conditions, and fusion application. Second, from a regional perspective, the development interaction between China's DIEI continued to improve from 2002 to 2017, regardless of the Eastern, Central, and Western regions or most provinces. During the study period, the Eastern region scored the highest in the comprehensive fusion level of DIEI, the absolute gap between the Central, Western, and

Eastern regions widened, and the disparity between the provinces with the highest and lowest comprehensive fusion level was even greater. Third, the integrated development of DIEI showed a positive correlation with the development level of DI, EI, ST innovation, ER, and urbanization. Therefore, improvements in these fields can boost the integrated development of DIEI. Fourth, during the study period, in advancing the integrated development of China's DIEI, the influence of urbanization level was much higher than that of DI, EI, ST innovation, and ER. Among them, EI also played a significant role, DI still has a great potential that should be unleashed, and the impact of ER was the least. Fifth, empirical results confirm the existence of a significant, nonlinear, and U-shaped relationship between the fusion level of DIEI and the industrial structure level.

Findings from this study carry several major implications for China's industrial policies, resulting in the following recommendations. First, China should consolidate the foundation for the integrated development of DIEI and advance the rapid and healthy development of the fusion in the two industries. The country should encourage investment and construction in key areas such as 5G, cloud technology, data centers, and industrial Internet. The country should also improve the laws and regulations related to the integrated development of DIEI, cultivate the required compound talents, and establish a perfect digital governance system. Second, it is highly recommended that China strengthen the cooperation between different regions in the fusion of DIEI to reduce the regional development disparity in this field. The Chinese government is advised to introduce differentiated digital energy support policies based on the advantages and characteristics of different regions. Third, China should optimize the top-level design and overall layout and build a technological innovation system that conforms to the market changes of the integrated development of DIEI. Additionally, China should establish data trading places and explore innovative models such as data capitalization and cross-border circulation trading. Fourth, the country should give further play to the significant role of urbanization in promoting the fusion of DIEI, by reforming the registered residence system, advancing the citizenization of the agricultural transfer population, and raising public services level; thus, creating advantageous conditions for the integrated development of the two industries. Fifth, the country should aim to optimize the industrial structure and constantly advance the rationalization, upgrading, and greening of it. From focusing on the scale growth of the secondary and tertiary industries to paying greater attention to the growth quality of the primary, secondary, and tertiary industries, China should design and implement an industrial structure that conforms to the integrated development of DIEI.

CRediT authorship contribution statement

Wang J.: Investigation, Originality, Data curation, Original Draft, Writing - Review & Editing.

Nghiem X.: Investigation, Methodology, Original Draft, Writing - Review & Editing, Visualization.

Jabeen F.: Computation, Writing - Review & Revising, Supervision.

Luqman A.: Writing - Review & Editing, Visualization.

Song M.: Validation, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Data availability

Data will be made available on request.

Acknowledgments

This study was supported by the National Natural Science Foundation of China (Grant Nos. 71934001, 71471001, 41771568, and 71533004), the National Key Research and Development Program of China (Grant No. 2016YFA0602500), and the Strategic Priority Research Program of Chinese Academy of Sciences (Grant No. XDA23070400).

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Wang J. is a PhD student at School of Economics of Fujian Normal University and works at School of Ecological Environment and Urban Construction of Fujian University of Technology. His research interesting focuses on digital economy, energy and environmental policy.

Nghiem X. is a Lecturer Faculty of Economics and Management, International School, Vietnam National University, Hanoi, Vietnam.

Jabeen F. is a Professor of Management at the College of Business at Abu Dhabi University, UAE. She has published in leading journals like International Journal of Hospitality Management, Knowledge Management Research & Practice, Journal of Cleaner Production, Business Strategy and the Environment, Technological Forecasting and Social Change, Applied Psychology: Health and Well-Being, and IEEE Transactions on Engineering Management. She has been honored with the 'Outstanding Paper Award' and 'Highly Commended Paper' in the 2018 and 2019 Emerald Literati Awards and Abu Dhabi University Research Fellow Award 2018.

Luqman A. holds a Ph.D. in Business Administration (major in information systems management) from the University of Science and Technology of China. He is currently working as a research professor at Shenzhen University, China. He is an active referee for several well-known publishers (ELSEVIER, WILEY, TAYLOR & FRANCIS, SAGE, etc.). He has published more than 25 papers in leading international journals such as Information & Management, Journal of Business Research, Computers in Human Behavior, Technology in society, and International Journal of Human-computer interaction.

Song M. is Professor at Anhui University of Finance and Economics. He holds PhD in Economics from University of Science and Technology of China. He focuses on the efficiency and productivity analysis. He has published in outlets, such as European Journal of Operational Research, Journal of Environmental Management, International Review of Financial Analysis, Scientific Data, Technological Forecasting & Social Change, Annals of Operations Research, China Economic Review, Energy Policy, Journal of Productivity Analysis, among others.