



Towards inclusive green growth: does digital economy matter?

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Received: 22 March 2023 / Accepted: 27 April 2023 / Published online: 6 May 2023
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Abstract

In this decade, China has been pursuing an inclusive green growth strategy. Concurrently, the digital economy, which relies on the Internet of Things, big data, and artificial intelligence, has experienced explosive growth in China. The digital economy's capacity to optimize resource allocation and reduce energy consumption potentially makes it a conducive channel towards sustainability. Using the panel data of 281 cities in China from 2011 to 2020, we theoretically and empirically explore the impact of the digital economy on inclusive green growth. Firstly, we theoretically analyze the potential impact of the digital economy on inclusive green growth using two hypotheses: accelerating green innovation and promoting the industrial upgrading effect. Subsequently, we measure the digital economy and inclusive green growth of Chinese cities using Entropy-TOPSIS and DEA approaches, respectively. Then, we apply traditional econometric estimation models and machine learning algorithms to our empirical analysis. The results show that China's high-powered digital economy significantly promotes inclusive green growth. Moreover, we analyze the internal mechanisms behind this impact. We find that innovation and industrial upgrading are two plausible channels that explain this effect. Additionally, we document a nonlinear feature of diminishing marginal effects between the digital economy and inclusive green growth. The heterogeneity analysis shows that the contribution weight of the digital economy to inclusive green growth is more remarkable in eastern region cities, large and medium-sized cities, and cities with high marketization. Overall, these findings shed more light on the digital economy-inclusive green growth nexus and provide new insights into understanding the real effects of the digital economy on sustainable development.

Keywords Digital economy · Inclusive green growth · Machine learning · Innovation

Introduction

The global spread of COVID-19 has brought great shock to the economic systems worldwide. Meanwhile, it also triggers a vigorous digital economy boom. The digital transformation of various industries injects new drivers into global economic growth (Bunje et al. 2022; Hosan et al. 2022). In 2021, the value added of the digital economy in 47 countries reached US \$38.1 trillion, with a year-on-year nominal growth rate of 15.6%, accounting for 44 percent of GDP.¹ Specifically, the USA and the European Union have been relying on leading technological innovation to build a global economy of digital superiority (Ma and Zhu 2022). Notably, as a population superpower and the world's second-largest economy, China also leads the world in the scale of its digital economy (Lyu et al. 2023). Data is a new factor of production in the context of the digital economy, which has brought about profound changes in production,

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¹ https://news.dayoo.com/china/202211/10/139997_54381695.htm.

consumption, exchange, and distribution. The digital economy's scale effect, low transaction cost, and wide penetration are the most essential properties that influence the “inclusive” and “green” components (Asongu et al. 2021; Shahbazab et al. 2022).

Inclusive green growth denotes achieving a growth trajectory that is socially progressive and environmentally sustainable, such that natural assets continue to provide the resources and environmental services on which life depends (Ofori et al. 2022a, b; Khan et al. 2022). In addition, it emphasizes the balanced relationship among the economy, society, and environmental systems (Fan et al. 2022). China has achieved remarkable achievements since the reform and opening-up policy. In 2021, China's GDP reached 17.7 trillion US dollars, accounting for 18.5% of the world's total.² However, behind this boom lies a series of serious problems. For instance, the huge urban–rural income gap, inequality of social opportunities, and environmental pollution (Gu et al. 2021). If these problems continue to spread without prompt management, they will hinder sustained economic growth in China. Existing studies (Stiglitz 2016; Armeanu et al. 2018; Fan et al. 2022) have proposed that continuously deteriorating social inequality and environmental issues may lead to a slowdown in economic growth. Also, it may bring social unrest, which is not conducive to China's realization of sustainable development goals in the future.

To tackle these issues and difficulties encountered in the pace of inclusive green growth, many scholars have focused on the potential drivers of inclusive green growth from different dimensions, such as urbanization, foreign direct investment, and financial development (Fan and Liu 2022; Fan et al. 2022). However, the impact of a digital economy as the main economic pillar after the agricultural economy and industrial economy has not been sufficiently investigated in the context of inclusive growth (Shahbazab et al. 2022). Since advanced digital technologies such as the Internet of Things (IoT), artificial intelligence, and blockchain are dramatically changing economic structures, it is important to assess the role of digital economic development in inclusive green growth. Advanced digital technologies are now being closely integrated with the real economy and are changing the competitive landscape of the world. Additionally, with its strong geographical penetration, it can provide mobile health care, mobile education, and other services to residents in remote areas, helping to promote equality of opportunity (Asongu et al. 2021; Dutta et al. 2019). Furthermore, the digital economy platforms offer opportunities to the bottom of the pyramid's (BOP) entrepreneurship activities (Gupta and Kanungo 2022). Moreover, digital technologies are integrated with traditional manufacturing systems to build a new

energy ecosystem, improving energy efficiency and reducing pollutant emissions (Shahbazab et al. 2022).

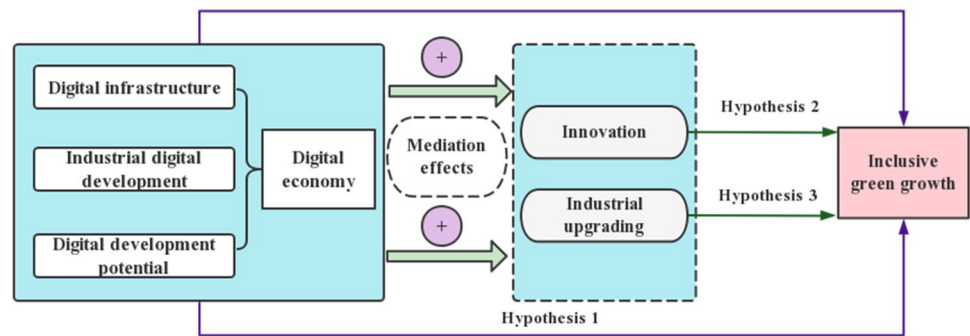
Existing literatures have studied the impact of the digital economy on a single aspect of inclusive green growth, such as the economy, society, or environment, but there are very few researches devoted to the study of the digital economy on inclusive green growth. The Chinese government has regarded inclusive green growth as a major national development strategy in recent years. Meanwhile, thanks to the effect of China's population size, the digital economy has achieved remarkable development. Exploring the impact of China's digital economy on inclusive green growth is very important for the Chinese government to formulate scientific policy solutions. However, the literature focusing on the relationship between China's digital economy and inclusive green growth is insufficient. How the digital economy influences inclusive green growth in China is still an empirical puzzle that needs to be further investigated. To this end, we aim to fill the research gap by addressing the following questions: Can the digital economy in Chinese cities positively impact inclusive green growth? Does the digital economy play the role of the main engine for inclusive green growth in Chinese cities? What economic channels shape it? Is this relationship characterized by heterogeneity?

In this context, assessing the impact of the development of the digital economy on inclusive green growth is crucial for nations around the world, especially developing countries, to achieve their sustainable development goals. Using the panel data of 281 prefecture-level cities in China from 2011 to 2020, this study empirically examines the impact of the digital economy on inclusive green growth. First, we establish a theoretical framework for the impact of the digital economy on inclusive green growth. Secondly, we measure the digital economy and inclusive green growth levels using the Entropy-TOPSIS method and the DEA model, respectively. Furthermore, we apply econometric models and a nest of machine learning algorithms to empirically analyze the relationship between the digital economy and inclusive green growth and examine the economic mechanisms. We find that the digital economy substantially promotes inclusive green growth. We also explore the potential economic channels through which the digital economy stimulates inclusive green growth. Our mediation analysis shows that innovation and industrial upgrading are two plausible mechanisms through which the digital economy enhances inclusive green growth. In addition, we also conducted nonlinear relationship tests and heterogeneity analysis to obtain more detailed conclusions.

The main contribution of our study is summarized in the following three aspects. First, we make the first attempt to check the potential influence of the digital economy on inclusive green growth in China. Existing studies have only unsystematically focused on fragmented elements of digital

² <http://www.mnw.cn/news/cj/2593503.html>.

Fig. 1 The conceptual framework of the digital economy on inclusive green growth



technologies such as ICT, the Internet, and artificial intelligence (AI) in promoting inclusive green growth (Asongu et al. 2021; Goralski and Tan 2022). These focused on these individual components, possibly due to data availability. These drivers of inclusive green growth are partial elements of the digital economy and are not equal to the digital economy. Based on these prior studies' findings, it is difficult to make a case for the digital economy; hence, we systematically analyzed how a digitized economy impacts green growth using a holistic approach. To the best of our knowledge, studies that investigate the potential impact of the digital economy on inclusive green growth are scarce. Thus, our study provides a valuable reference for policymakers in China and other developing economies to formulate policies to promote inclusive green growth from a digital economy perspective.

Second, in addition to assessing the impact of the digital economy on inclusive green growth using traditional econometric models, we introduce advanced machine learning algorithms into the empirical tests. One concern with the traditional econometric models is that the results are based on a large number of usually highly correlated variables and hence may give rise to the multicollinearity problem (Akbari et al. 2021). Using a broad set of correlated variables in the same model may yield inefficient coefficient estimates. In contrast, machine learning algorithms are very good at solving such problems. In addition, this approach clearly calculates the important weight of each explanatory variable's contribution to the dependent variable and explores the nonlinear relationship between the dependent and independent variables (Fan and Liu 2022). Our study also expands the literature that applies advanced machine learning algorithms to empirical research in economic and sustainable development.

Third, due to the differences in the digital economy and inclusive green growth levels across different cities in China, this study creatively discusses the regional heterogeneity and asymmetry effects of digital economy development on inclusive green growth. As a result, more concrete and practical policies can lay solid policy support for the accelerated transformation of inclusive green growth. While other

relevant studies (Nchofoung and Asongu 2022; Olufemi and Adeyemi 2020) only analyzed the overall relationship between related variables without detailed heterogeneity analysis in developed countries, their conclusions drawn on this basis are more general.

The rest part of the study is organized as follows. The "Theoretical framework and hypotheses" section describes the theoretical framework and hypotheses of our manuscript. The "Data, variables, and methodology" section introduces the data, variables, and methodology of this study. The "Main findings" section presents the main findings. The "Heterogeneity analysis" section conducts heterogeneity analysis. Finally, the "Conclusions and policy implication" section draws conclusions and policy implications.

Theoretical framework and hypotheses

Drawing towards inclusive green growth is one of the primary tasks faced by all nations worldwide in the transition to a sustainable development society (Fan et al. 2022; Ofori et al. 2022a, b). In our study, we propose that the digital economy is the main engine that significantly enhances inclusive green growth in China. We aim to provide more systematic and reliable evidence on the impact of the digital economy on inclusive green growth in China. In this regard, this paper demonstrates the logical mechanisms of the digital economy for inclusive green growth. Figure 1 exhibits the conceptual framework and hypotheses of our study.

Digital economy and inclusive green growth

The literature on the relationship between the digital economy and inclusive green growth principally focuses on the impact of the digital economy on the individual sustainable development goal emphasized by the UN in 2015. In this connection, related literature that follows is divided into three principal strands: the economic, social, and environmental views of the goals. The first strand of literature investigates the relationship between the digital economy and economic growth. In fact, recent growth theories have

acknowledged the essence of digital technology for economic growth. The effect of the digital economy on growth is through its strengthening influence on enhancing financial inclusion (Kouladoum et al. 2022; Tay et al. 2022), driving entrepreneurship (Afawubo And Noglo 2022), and promoting globalization (Andrew Petersen et al. 2022). However, Albiman and Sulong (2017) argued that the digital economy could become unfavorable to the economy, especially in the absence of economic transformation.

Away from the economic dimension, the digital economy has multiple effects on social development. In this respect, the digital economy could boost inclusive growth through its extensive permeability and low marginal cost for promoting education and medical opportunities. For instance, Asongu et al. (2021) document the significant role ICT deepening plays in advancing inclusive education through policies that reduce poverty and income inequality. Dutta et al. (2019) propose that digital technologies could boost the decentralization of health systems by reducing geographical constraints and bringing healthcare providers and beneficiaries closer. Meanwhile, some studies argue that ICT could bridge the income gap and adjust income distribution among different regions within a nation (Wang and Wright 2020; Zhu et al. 2022). Similarly, Goralski and Tan (2022) suggest that artificial intelligence (AI) could help humanity achieve the ambitious goal of eradicating extreme poverty. Moreover, people in poor regions could carry out entrepreneurial activities through digital platforms, such as e-commerce, which could also improve the human capital level of low-income families through online knowledge sharing; thus, the digital economy would narrow the income gap.

Equally, a digital economy for inclusive green growth can be achieved through the environmental dimension. However, the environmental impact of the digital economy is controversial. On the one hand, the platform model under the digital economy advocates online trading and payments, which can reduce the travel costs and transaction costs of enterprises and households in terms of carbon emissions (Yi et al. 2022; Asongu et al. 2018). In addition, the digital economy can save energy and reduce carbon emissions by developing smart energy systems, smart industries, and smart cities (Avom et al. 2020). However, on the other hand, the ICT that serves the digital economy needs to consume energy in use, leading to the growth of carbon emissions (Avom et al. 2020). Meanwhile, the digital economy has driven the inclusion of financial services, led to the growth of investment and consumption activities, and promoted carbon emissions (Qin et al. 2022; Li et al. 2020). Therefore, the digital economy may positively or negatively impact the environment.

In general, the positive association between the digital economy and inclusive green growth can be derived from the following reasons. First, the digital economy could promote

financial inclusion, globalization, and entrepreneurship, thus stimulating growth in the economic system. Meanwhile, a rise in digital resource allocation and better application of ICT is also associated with equal educational and medical opportunities for people. Thus, the poor reduction effect and income gap narrowing effect will happen through the digital economy. Additionally, the digital economy plays a positive role in environmental protection by reducing energy consumption and carbon emissions and promoting the production of cleaner technologies. Based on the theoretical arguments and previous research outcomes, we formulate the following hypothesis:

Hypothesis 1. Digital economy is conducive to the improvement of inclusive green growth in Chinese cities.

Digital economy, innovation, and inclusive green growth

The endogenous growth theory regards technological progress driven by innovation as the main engine to propel sustainable economic growth. The greater integration of advanced digital technology and the substantial economy leads to the gradual transformation of the growth model from factor-driven to innovation-driven (Zhu and Chen 2022). Existing studies document that this evolution is a prerequisite for achieving inclusive green growth (Ren et al. 2022). Therefore, this study argues that the digital economy promotes inclusive green growth by improving the level of innovation.

Furthermore, the essential attribute of the digital economy has strong innovation characteristics (Pan et al. 2022; Horoshko et al. 2021). The digital industry based on the Internet of Things, artificial intelligence, blockchain, cloud computing, and other digital technologies has a high knowledge density and innovation capability (Horoshko et al. 2021). When these technologies are introduced into traditional industries, new business models, industrial processes, and products will be developed. The innovation of the industry in these aspects can not only reduce energy consumption and pollutant emissions (Yang et al. 2022; Kahouli et al. 2022) but also improve the business performance of the industry to drive economic growth and provide more employment opportunities (Oyinlola et al. 2021). Additionally, the digital economy could lessen enterprises' production costs, search costs, matching costs, and other transaction costs (Istrateanu and Gheorghe 2021). For instance, introducing digital quality control systems to manufacturing enterprises will improve production efficiency and product quality and reduce production costs (Istrateanu and Gheorghe 2021). Mitigating information asymmetry is the main way to reduce enterprises' search and matching costs in the digital economy (Miao 2021).

Generally, the digital platform has a large amount of producer and consumer data and carries out accurate matching, accurate trading, and accurate evaluation for both parties, thus saving transaction costs (Bogachov et al. 2021). As the operating costs of enterprises continue to decrease, the saved funds will be invested in R&D expenses and innovative activities to improve the level of inclusive growth. In addition, digital networks connect a large scale of innovative entities, which can exert a scale effect (Sedighi et al. 2022). The exchange mode of value sharing and development has narrowed the distance between innovation subjects and expanded the scale of innovation groups. According to Metcalfe's law, the value of digital platforms is proportional to the square of the number of users. Thinking collisions and brainstorming among users have become the norm, which broadens innovative thinking, creates an open innovation situation, and thus improves the overall innovation level (Olufemi and Adeyemi 2020). Therefore, we propose the following hypothesis:

Hypothesis 2. Digital economy can facilitate inclusive green growth by accelerating innovation.

Digital economy, industrial upgrading, and inclusive green growth

We also investigate the mechanisms through which the digital economy influences inclusive green growth by examining the transmission channel of industrial upgrading. Industrial upgrading refers to the process or trend of transforming the industrial structure from a low-level technology-based form to a high-level technology-driven form (Tian et al. 2021). The digital economy fully enables the transformation and upgrading of traditional industries and promotes the transformation of low-value-added industries to high-tech and high-value-added industries. The existing research has confirmed that industrial upgrading can promote inclusive green growth (Fan et al. 2022; Fan and Liu 2022).

On the one hand, the development of the digital industry and the increase in market share are essential components of industrial upgrading. Since the birth of the third scientific and technological revolution in the human world, after more than 30 years of development, the information service industry, the software industry, the Internet of Things industry, and the artificial intelligence industry have been booming (Horoshko et al. 2021). The proportion of these industries in the national economy continues to rise, such as the sharing economy, platform economy, e-commerce, and other business models that are widely popular (Tran et al. 2022; Cantarella and Strozzi 2022). On the other hand, digital technology enables traditional industries to become more "green" and "advanced." For example, the manufacturing industry takes data as a production factor,

and the production process and technology become more intelligent, reducing the low efficiency and cost of the production process (Rodríguez-Espíndola et al. 2022). In this context, the extensive and high-energy traditional industry has gradually transformed into an intensive and intelligent industry. In addition, the digital economy has a strong interconnection characteristic, realizing the networking of producers and supply chains. All participants can directly connect with value chain partners, accurately capture consumer market demand changes, and timely adjust and optimize product strategies, thus promoting high-end production. In short, industrial upgrading will eliminate high energy consumption and high-pollution industries and encourage green growth. Similarly, industrial upgrading can facilitate the agricultural population transfer to the nonagricultural sector, increase the social employment rate, narrow the gap between urban and rural areas, and make society more inclusive (Fan and Liu 2022). Hence, we argue the following hypothesis:

Hypothesis 3. Digital economy can enhance inclusive green growth through promoting industrial upgrading.

Data, variables, and methodology

Data

The dataset utilized in our study is a balanced panel covering 281 cities in China for the period 2011–2020. And the original data is derived from the *China City Statistical Yearbook*, *China Rural Yearbook*, *China Information Industry Yearbook*, the *Government Statistics Bureau website*, *China Environmental Statistical Yearbook*, and the *Wind database*. We fill in some missing values using a linear interpolation method and manual calculation to obtain a balanced urban panel dataset.

Variables

Measurement of inclusive green growth

Our core dependent variable is inclusive green growth (IGE). Motivated by the related literature measuring inclusive growth (Fan and Liu 2022), we employ the slacks-based DEA model (SBM-DEA) by including undesirable outputs as well as coupling it with the global Malmquist-Luenberger (GML) productivity index to calculate IGE (Ma and Zhu 2022). The strength of this approach is that it measures inclusive green growth from an efficiency perspective, taking into account both input and output aspects (Fan and Liu 2022). Our computation proceeds of IGE are as follows:

Table 1 Comprehensive index system of the digital economy

Target level	Sub-dimension	Indicator	Attribute
Digital economy	Digital infrastructure	Number of households using the Internet per 10,000 households	Positive
		Number of mobile phone base stations (unit: 10,000)	Positive
		Number of mobile phones per 10,000 population	Positive
		Number of fixed-line telephones installed per 10,000 households	Positive
	Industrial digital development	Total telecom business per capita (ten thousand yuan/person)	Positive
		Proportion of e-commerce sales to GDP	Positive
		Proportion of software business income to GDP	Positive
	Digital development potential	Proportion of information service industry to GDP	Positive
		Proportion of science spending in the financial budget	Positive
		Number of college students per 10,000 population	Positive
		Proportion of ICT practitioners to the total employees	Positive
		Number of high-tech enterprises engaged in ICT	Positive

(i) Global production possibility set (GPPS). Suppose each city is a decision-making unit (DMU). In addition to the desirable output, such as GDP, it will inevitably generate some undesirable outputs, such as pollutant emissions and income gap. Assume every DMU includes N kinds of inputs $x_{in} = (x_{i1}, x_{i2}, \dots, x_{iN}) \in R_N^+$, it generates M kinds of desirable outputs $y_{im} = (y_{i1}, y_{i2}, \dots, y_{iM}) \in R_M^+$, as well as K kinds of undesirable output $b_{ik} = (b_{i1}, x_{i2}, \dots, b_{iK}) \in R_K^+$. Then, we could obtain the following GPPS:

$$P^G(x) = \left\{ \begin{array}{l} (y^t, b^t) : \sum_{i=1}^T \sum_{m=1}^M \beta_i^t y_{im}^t \geq y_{im}^t, \forall m; \sum_{i=1}^T \sum_{k=1}^K \beta_i^t y_{ik}^t, \forall k; \\ \sum_{i=1}^T \sum_{m=1}^M \beta_i^t y_{im}^t \leq y_{im}^t, \forall m; \sum_{i=1}^T \sum_{k=1}^K \beta_i^t = 1, \beta_i^t \geq 0, \forall i \end{array} \right. \quad (1)$$

(ii) Global SBM directional distance function (SBM-DDF). The input–output is $(x^{t,i}, y^{t,i}, b^{t,i})$, and the direction is (g^x, g^y, g^b) , as well as the relaxation vector is (s_n^x, s_m^y, s_k^b) . And each cross-section weight is denoted as z_i^t . We could obtain the global SBM-DDF by

$$S_v^G(x^{t,i}, y^{t,i}, b^{t,i}, g^x, g^y, g^b) = \max \frac{\frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{g_n^x} + \frac{1}{M+K} \left(\sum_{m=1}^M \frac{s_m^y}{g_m^y} + \sum_{k=1}^K \frac{s_k^b}{g_k^b} \right)}{2} \quad (2)$$

$$\begin{aligned} s.t. \quad & \sum_{i=1}^T \sum_{m=1}^M z_i^t x_{im}^t + s_n^x = x_{in}^t, \forall n; \\ & \sum_{i=1}^T \sum_{m=1}^M z_i^t x_{im}^t - s_{nm}^x = y_{im}^t, \forall m; \\ & \sum_{i=1}^T \sum_{k=1}^K z_i^t x_{ik}^t + s_i^b = b_{ik}^t, \forall i; \\ & \sum_{i=1}^T z_i^t = 1, z_i^t \geq 0, \forall i; \\ & s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \end{aligned}$$

(iii) GMI index and IGE. The advantage of SBM-DDF is that it eliminates the problems of linear programming misunderstanding (Ma and Zhu 2022). Furthermore, this approach takes into account the changes in the efficiency

values at time t and time $t + 1$ so it can monitor the dynamic characteristics of IGE and improve the accuracy of the results (Oh 2010). Its equation is expressed as follows:

$$IGE_t^{t+1} = GML_t^{t+1} = \frac{1 + S_v^G(x^t, y^t, b^t, g^x, g^y, g^b)}{1 + S_v^G(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b)} \quad (3)$$

where the global DDF is denoted as $S_v^G(\bullet)$, and the dynamic variation of IGE between time t and time $t + 1$ is measured by the GML index.

Furthermore, to evaluate the level of inclusive green growth, we incorporate input variables, desirable output variables, and undesirable variables to calculate IGE. Referring to existing literature (Fan and Liu 2022; Ma and Zhu 2022), we consider labor, capital, and electricity consumption as input variables. And the output variable contains the desirable output as the GDP of the economic system, the undesirable output as the urban–rural income gap in the social system, as well as the sulfur dioxide emissions in the environmental system.

Measurement of the digital economy

Our core independent variable is the digital economy (Dei). Existing researches usually utilize ICT as a proxy variable for the digital economy (Zhu and Chen 2022; Asongu et al. 2021). However, ICT mainly focuses on digital technology; it cannot describe the level of the digital economy’s development fully. Motivated by this, we construct a more rounded index system to evaluate the level of the digital economy at the city level in China. Based on this, we employ the Entropy-TOPSIS approach to measure the digital economy index. The index system of the digital economy is shown in Table 1, and its calculation steps are as follows:

(1) The index X_{ij} of the digital measure index system is treated with the same direction of index attributes, the indicators are selected to be positive, and the processed indicators are denoted as Y_{ij} .

$$Y_{ij} = \begin{cases} \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})}, & X_{ij} \text{ is a positive indicator} \\ \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})}, & X_{ij} \text{ is a negative indicator} \end{cases} \quad (4)$$

where i denotes the city, j presents the measurement indicator, $\max(X_{ij})$ and $\min(X_{ij})$ denotes the maximum value and the minimum value of X_{ij} .

(2) To standardize with Y_{ij} , to eliminate the inconsistency in dimensions of different measurement indicators, the standardized indicators are recorded as Z_{ij} .

$$Z_{ij} = \frac{Y_{ij}}{\sum_{i=1}^n Y_{ij}}, \quad i = 1, 2, \dots, n, \quad j = 1, 2, \dots, m \quad (5)$$

$$Z^+ = (\max\{Z_{11}, Z_{21}, \dots, Z_{n1}\}, \max\{Z_{12}, Z_{22}, \dots, Z_{n2}\}, \dots, \max\{Z_{1m}, Z_{2m}, \dots, Z_{nm}\}) = (Z_1^+, Z_2^+, \dots, Z_m^+) \quad (8)$$

The min value of each indicator element constitutes the worst alternative Z^- .

$$Z^- = (\min\{Z_{11}, Z_{21}, \dots, Z_{n1}\}, \min\{Z_{12}, Z_{22}, \dots, Z_{n2}\}, \dots, \min\{Z_{1m}, Z_{2m}, \dots, Z_{nm}\}) = (Z_1^-, Z_2^-, \dots, Z_m^-) \quad (9)$$

distance d_1^- between the opinion target and the worst alternative Z^- .

$$d_1^+ = \sqrt{\sum_{j=1}^m (Z_{ij} - Z_j^+)^2} \quad (10)$$

$$d_1^- = \sqrt{\sum_{j=1}^m (Z_{ij} - Z_j^-)^2} \quad (11)$$

(7) By calculating the proximity between each opinion target and the optimal alternative, we could obtain the digital economy index Dei_i by the following equation:

$$Dei_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (12)$$

where $0 \leq C_i \leq 1$; the greater the value of C_i indicates the better performance of the digital economy of the city. Conversely, the smaller the value of C_i means the poor performance of the digital economy of the city.

Figures 2 and 3 exhibit more details related to inclusive green growth efficiency and the digital economy index during the statistical period. Specifically, Fig. 2 displays the relative rank of the digital economy across 281 cities in 2011, 2016, and 2020. While Fig. 3a, b reveal the overall time trend of the digital economy

where n means the number of cities, and m denotes the number of indicators.

(3) To calculate the information entropy E_j of each measurement index Z_{ij} in the digital economy measurement index system after (1) and (2) processing:

$$E_j = -\frac{1}{\text{LN}(n)} \sum_{i=1}^n Z_{ij} \text{LN}(Z_{ij}), \quad j = 1, 2, \dots, m \quad (6)$$

(4) To calculate the weight of the j -th indicator, as w_j

$$w_j = \frac{1 - E_j}{\sum_{i=1}^m (1 - E_i)}, \quad j = 1, 2, \dots, m \quad (7)$$

(5) To confirm the optimal alternative Z^+ and the worst alternative Z^- .

The max value of each indicator element constitutes the optimal alternative Z^+ .

(6) To calculate the distance d_1^+ between the opinion target and the optimal alternative Z^+ , as well as the

index and inclusive green growth efficiency at the national level, respectively. Cities with greener and bluer colors indicate higher digital economy ranking for that year in Fig. 2.

It can be observed in Fig. 2 that most of the cities in China were at a low level of digital economy development in 2011. Merely a few cities were at medium or high levels. Afterward, a dramatic change took place in 2016. During this year, several medium-level cities have significantly increased digital economy development. These cities are mainly located in the southeast of China, such as in the Pearl River Delta and Yangtze River Delta regions. The possible reason behind this phenomenon is that as China enters the new normal stage, the dynamism of growth has transformed into technology-driven and innovation-driven. Thus, the digital industrial upgrading with high tech shows explosive growth. Subsequently, medium- and high-level cities expand further and occupy the majority in 2020. Moreover, the global outbreak of COVID-19 has stimulated the explosive leap of the digital economy, and the digital industry has penetrated extensively in China.

Furthermore, Fig. 3a indicates that the digital economy development at the national level revealed is basically consistent with the above analysis. In addition, Fig. 3b displays

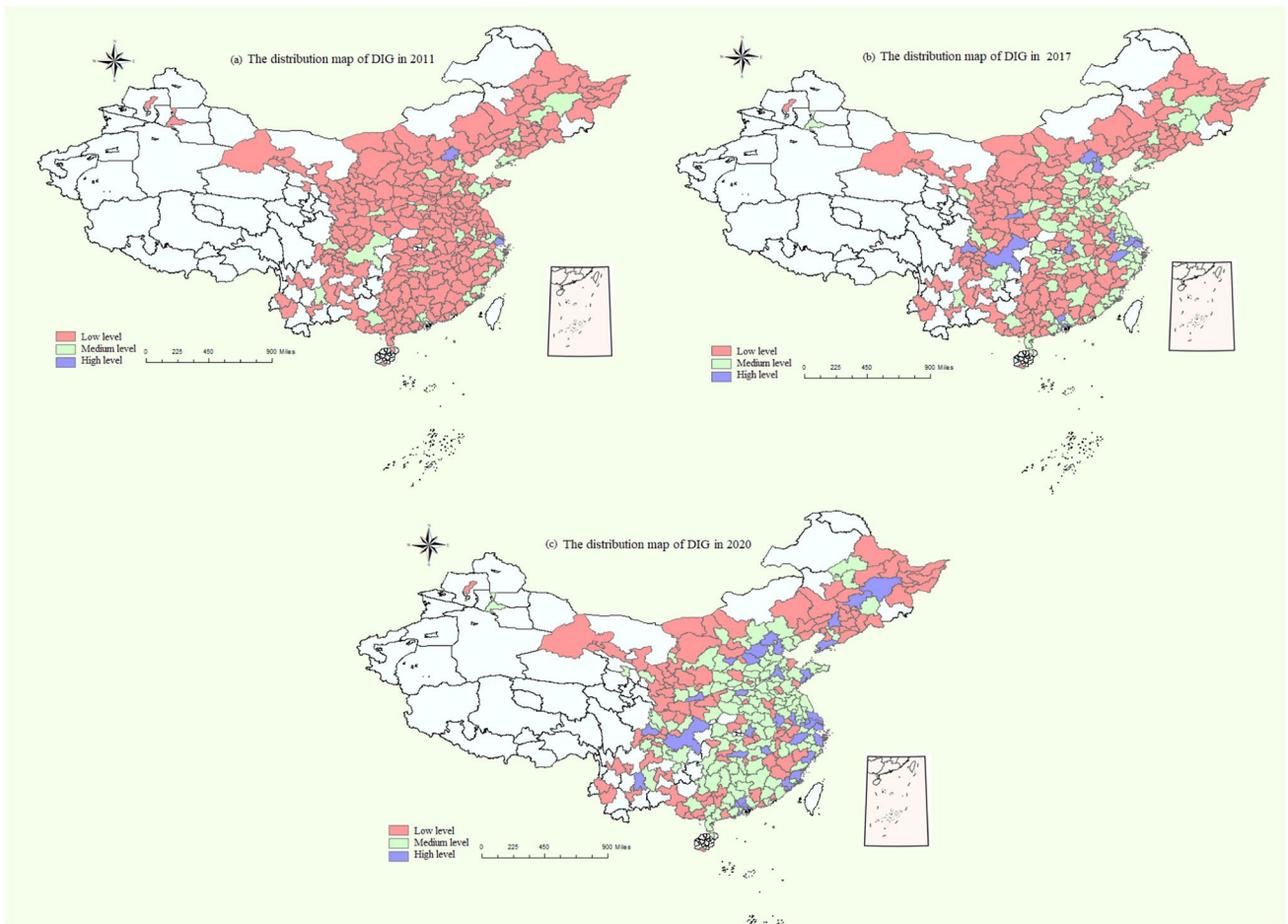


Fig. 2 Digital economy rank across cities in China

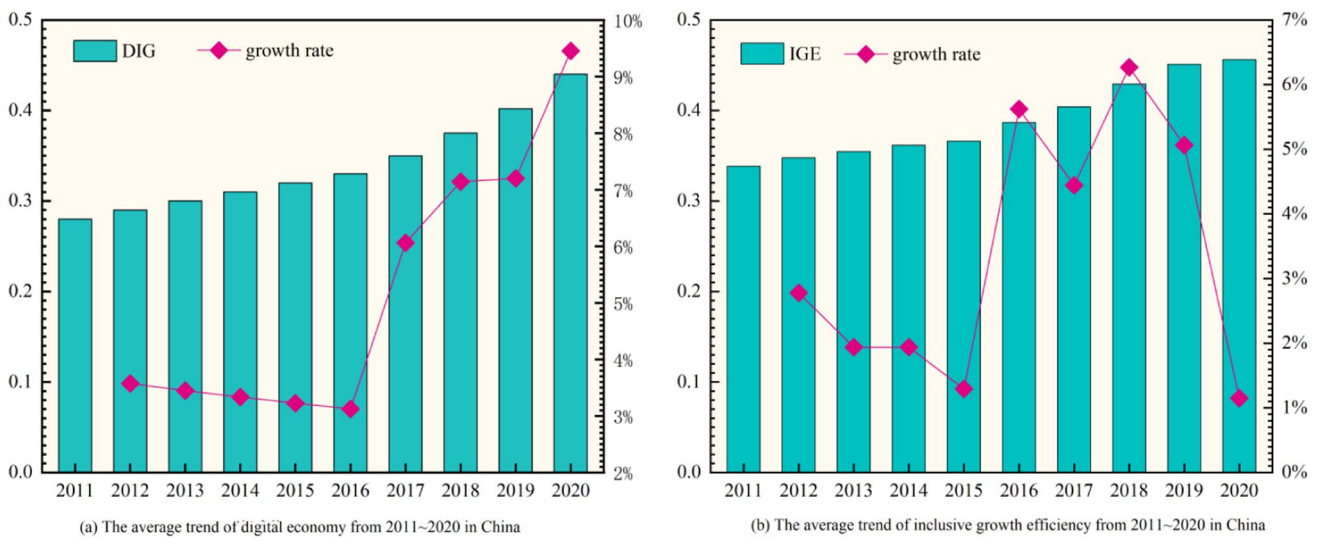


Fig. 3 Digital economy and inclusive green growth in China from 2011 to 2020

Table 2 The descriptive statistics of the variables

Variables	<i>N</i>	Mean	SD	Min	Max
DEI	2810	0.0338	0.0638	0.0020	0.8361
IGE	2810	0.3742	0.0669	0.2371	1.0292
FD	2810	3.6501	8.8063	0.9172	98.2921
URB	2810	0.2351	0.5011	0.0659	5.2891
FDI	2810	4.3291	0.8523	0.4772	6.4891
ED	2810	10.70	0.574	8.773	13.06
GI	2810	0.0243	0.0164	0.0035	0.0946

China's average inclusive green growth efficiency trend from 2011 to 2020. It can be divided into three stages: low-level development from 2011 to 2015, rapid development from 2015 to 2018, followed by a slowdown from 2019 to 2020. The second stage may have been driven by China's high-quality development strategy. During this period, China no longer simply pursues economic growth but also pays attention to the equality of social opportunities and the protection of the ecological environment. Therefore, the level of inclusive green growth shows a significant trend of improvement. In the third stage, the level of inclusive green growth has slowed down. The possible reason is that the global spread of COVID-19 has had a negative impact on the economy and society, which has adversely affected inclusive green growth.

Control variables

We turn our attention to the key control variables employed in the empirical analyses. These variables relate to city characteristics. Incorporating these control variables ensures that we evaluate whether city-specific elements could impact inclusive green growth in China separately. This will provide a sound basis for examining the primary determinants of inclusive green growth, focusing on within-city factors.

Particularly, we select the following control variables: (1) financial development (FD). We adopt the combined ratio of bank deposits and loan balance to GDP as a proxy for financial development. (2) Foreign direct investment (FDI). Referring to Fan and Liu (2022), we calculate the proportion of the foreign direct investment actually utilized in the city to the GDP. Then, we take a logarithmic treatment on it. (3) Urbanization (URB). We use the proportion of the city's real estate investment to regional GDP as a proxy. (4) Government intervention (GI). Referring to Ma and Zhu (2022), it is calculated using the proportion of fiscal expenditure to regional GDP. (5) Economic

development (ED). We apply the regional GDP divided by the city's total population as a proxy. The descriptive statistics of the variables are presented in Table 2.

Econometric methods

To investigate the impact of the digital economy on inclusive green growth, we construct the econometric model using the ordinary least square (OLS) method as the benchmark model, which is shown in Eq. (13), where IGE denotes our core dependent variable inclusive green growth; Dei_{it} represents the core independent variable digital economy in city i at the period t ; $Control_{it}$ means a series of control variables; the city and period fixed effects are expressed as μ_i and δ_t , respectively; and the random disturbance term is ε_{it} .

$$IGE_{it} = a_0 + a_1Dei_{it} + a_2Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (13)$$

Furthermore, we will examine whether innovation and industrial structure upgrading are the transmission channels through which the digital economy impacts the inclusive green growth of cities in China. Referring to Baron and Kenny (1986) and Hayes (2009), the mediating effect model is based on the stepwise regression method, which is expressed as follows:

$$MD_{it} = \beta_0 + \beta_1Dei_{it} + \beta_2Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (14)$$

$$IGE_{it} = \theta_0 + \theta_1Dei_{it} + \theta_2MD_{it} + \theta_3Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \quad (15)$$

The specific empirical test steps are as follows: first, we examine whether a_1 is significant. If it is significant, we will take the next step. Second, we tested whether β_1 is significant to verify whether the core explanatory variable significantly affected the intermediary variable. Third, we proceed to test the coefficients of θ_1 and θ_2 . If θ_1 becomes no longer significant while θ_2 significant, it indicates that the intermediary variable plays the role of a complete transmission channel; if θ_1 is still significant, but less than a_1 , and θ_2 is also significant, it indicates that the intermediary variable plays a partial role as the transmission channel.

Machine learning methods

To explore the nonlinear relationship between the digital economy and the inclusive green growth of cities in China, we apply a set of machine learning algorithms. In addition, this method could measure the digital economy's contribution to inclusive green growth. Whereas the econometric methods merely reveal the coefficient significance level of explanatory variables. Moreover, our advanced machine-learning algorithm can tackle a large number of highly

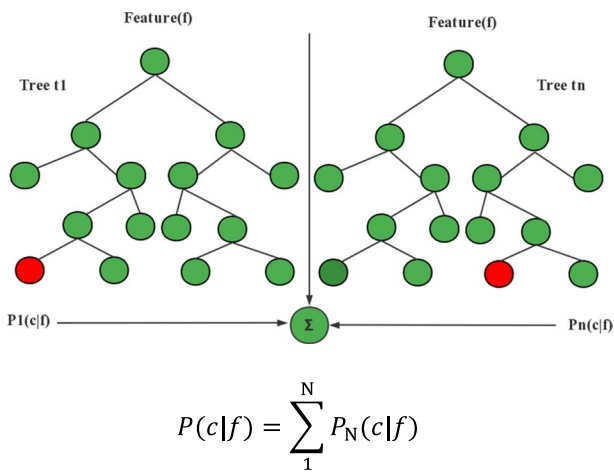


Fig. 4 Random forest algorithm

correlated explanatory variables and controls for multicollinearity (Akbari et al. 2021). Referring to Fan and Liu (2022), the following machine learning algorithm is adopted:

Random forest (RF)

RF is an extended variant of the bagging algorithm. It conducts sample training for multiple decision trees and belongs to a parallel machine learning integrated algorithm. The RF algorithm combines the results of multiple decision trees and randomly selects the dataset with random placement each time (Akbari et al. 2021). Thus, it comprehensively uses the prediction information of different decision trees and overcomes the limitations of a single tree to improve the robustness of prediction results. The idea of RF is shown in Fig. 4.

RF uses a subset of randomly selected independent variables to generate each decision tree. Therefore, it can not only be applied to a classification problem but also solve the regression problem in this study. The mathematical expression of RF is as follows:

$$\hat{Y} = \frac{1}{m} \sum_{i=1}^m g_k(x) \tag{16}$$

where \hat{Y} denotes the predicted value of the dependent variable; x means a vector of explanatory variables; $g(x)$ represents a nest of k -th learner random trees. RF gets the final calculation result by averaging the prediction results of each decision tree.

XGBoost

XGBoost is a classical integration algorithm for boosting ideas. It aims to continuously improve and enhance the basic learners and integrate them together to form a strong learner. The XGBoost algorithm continuously

generates new decision trees. The decision tree of each lesson is learned based on the difference between the last tree and the target value to reduce the model’s deviation (Fan and Liu 2022). Ultimately, the results of all decision trees are accumulated to complete the prediction process. The mathematical expression of the XGBoost algorithm is as follows:

$$\hat{Y} = \delta(x_i) = \sum_{i=1}^K f_k(x_i) \tag{17}$$

where \hat{Y} means the predicted value of the dependent variable; $f(x_i)$ denotes a decision tree. XGBoost performs the series operation through the iterative error. The XGboost algorithm conducts the second-order Taylor expansion of the loss function. It also adds the regular term to the objective function to balance the complexity of the objective function and the model. Thus, the XGBoost algorithm has the ability to deal with overfitting issues.

LightGBM

LightGBM is a distributed, high-performance gradient lifting framework based on a decision tree algorithm. LightGBM uses a leaf-wise algorithm with depth constraints. Its idea is to discretize continuous floating-point features into discrete values and construct a histogram with a width of k (Fan and Liu 2022). Then, traverse the training data and calculate the cumulative statistics of each discrete value in the histogram (Liang et al. 2020). With the same number of splits, leaf-wise can reduce the errors and improve the accuracy. It is expressed as follows:

$$\hat{Y} = \sum_{i=1}^T g_i(X) \tag{18}$$

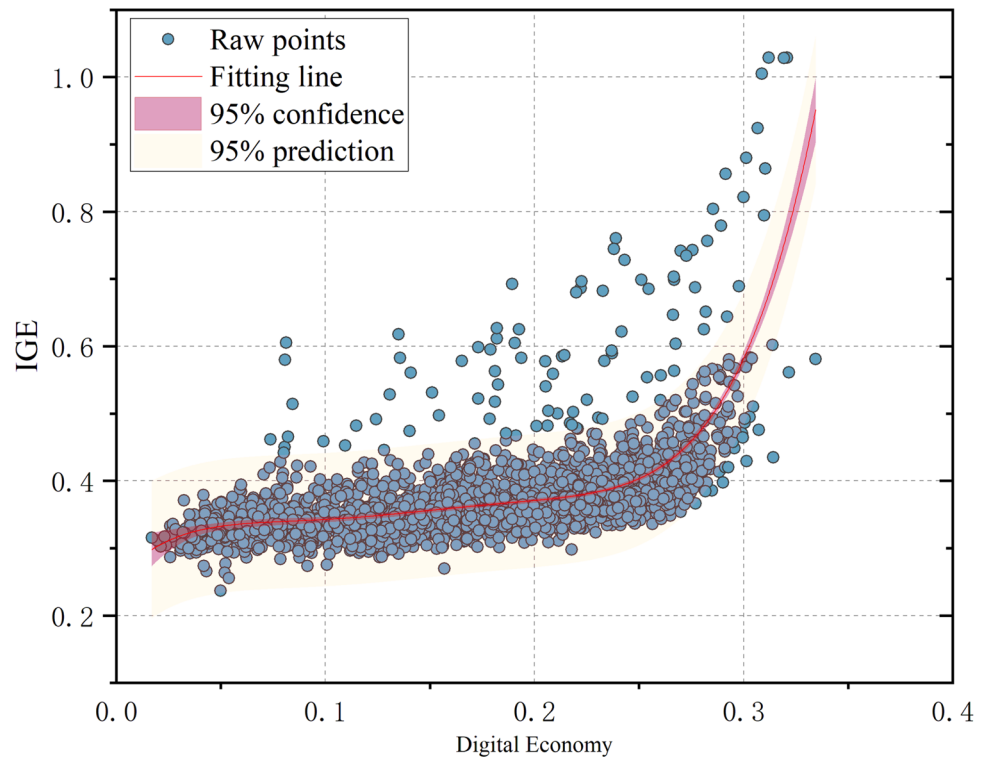
where LightGBM incorporates many T regression trees $\sum_{i=1}^T g_i(X)$ to estimate the final model (Ben Jabeur et al. 2021). Here, the regression trees may be shown as $w_p(x)$, where $p \in \{1, 2, \dots, M\}$. The variable M means the number of tree leaves, the decision rule of trees is p , and the leaf nodes’ sample weight is w (Ben Jabeur et al. 2021).

Main findings

Preliminary statistical analysis

To preliminary analyze the connection between the digital economy and inclusive green growth, we draw a scatter plot of Dei and IGE. Using the curve fitting toolbox in Origin software, we apply linear and quadratic functions to fit the linear and nonlinear relations

Fig. 5 Scatter plot between the digital economy and inclusive green growth



between Dei and IGE. The result is exhibited in Fig. 5. The horizontal axis represents the level of the digital economy, while the vertical axis is the level of inclusive green growth. It is easy to observe that there is no simple linear relationship between the two variables. The digital economy accelerates inclusive green growth when it goes beyond a certain range. However, this is only a preliminary statistical test of the relationship between the digital economy and inclusive green growth. A correlation does not mean a significant effect of the independent variable on the dependent variable. In addition, we have not incorporated other factors that may influence inclusive green growth in China. Therefore, the econometric models and machine learning models need to be further constructed in the following section to empirically test the impact of China's digital economy on inclusive green growth.

Test of the impact of the digital economy on inclusive green growth

In this subsection, we will employ econometric models and a set of machine learning algorithms to examine whether and how the digital economy development of cities in China impacts inclusive green growth and investigate the nonlinear relationship between them.

Baseline regression using a two-way fixed econometric model

We introduce the ordinary least-square (OLS) econometric model to estimate the coefficient of formulas (13)~(15). During this process, the city and year two-way fixed effects are incorporated. Meanwhile, the standard errors of the models are clustered at the city level. Table 3 presents the estimation results. Where column (1) takes Dei as the core independent variable, and IGE is the dependent variable. In columns (2)~(3), the dependent variables are innovation (INN) and industrial upgrading (IND), respectively. We adopt the logarithm of the number of patent applications as the proxy variable of INN. And we use the proportion of the added value of the tertiary industry in GDP as the proxy variable of IND. Their original data come from the *Chinese City Statistical Yearbook*. Furthermore, columns (4)~(5) take IGE as the dependent variable, we will focus on the coefficient of Dei, INN, and IND to investigate the transmission path of the impact of Dei on IGE.

It can be observed that the estimated coefficient of Dei in column (1) is positive and highly significant at the 1% statistical level, indicating the digital economy of cities in China may exert a positive impact on inclusive green growth under a linear model setting. While other control variables' coefficients are smaller than Dei, that affirms the digital

Table 3 The estimation results of baseline regression

	(1)	(2)	(3)	(4)	(5)
	IGE	INN	IND	IGE	IGE
DEI	0.8713*** (0.0726)	0.2031*** (0.0360)	0.3685*** (2.0178)	0.4476*** (0.0691)	0.3731*** (0.0597)
INN				0.2305*** (0.0369)	
IND					0.2265*** (3.6025)
FD	0.0062* (0.0036)	0.0017 (0.0016)	0.0609 (0.0739)	0.0060* (0.0035)	0.0037 (0.0033)
FDI	0.0007 (0.0128)	0.0009 (0.0013)	0.0254 (0.0163)	−0.0003 (0.0127)	−0.0006 (0.0126)
URB	−0.0064 (0.0627)	−0.0019 (0.0019)	0.0341 (0.1039)	−0.0065 (0.0617)	−0.0036 (0.0562)
GI	−0.1178** (2.1646)	−0.0906 (9.9916)	−0.9214*** (7.6855)	−0.6385* (2.5837)	−0.3606 (2.0580)
ED	−0.0017 (0.0592)	−0.0012** (0.0055)	0.1001* (0.0592)	−0.0020 (0.0591)	0.0005 (0.0581)
_CONS	0.33460*** (0.0598)	0.01196** (0.0548)	−0.90423 (0.6057)	0.33716*** (0.0595)	0.31705*** (0.0590)
City fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	yes	yes	yes	Yes	yes
Observations	2810	2810	2810	2810	2810
R ²	0.6682	0.6260	0.6456	0.7292	0.7836

***, **, and * denote 1%, 5%, and 10% significance levels, respectively. Robust standard errors in parentheses

economy as the main engine for inclusive green growth in China. Then, we uncover the mediating effects of innovation and industrial upgrading in columns (2)~(5) in Table 3. Accordingly, that will shed light on the indirect impacts of the digital economy on inclusive green growth.

Table 3, columns (2) and (3) indicate that the digital economy is positively associated with cities’ innovation level and industry upgrade. These results are consistent with the findings of Hao et al. (2023). They argue that the digital economy allows firms to invest in innovative activities on the microlevel and promote industrial structure optimization on the macrolevel. Furthermore, it is important to note that in Table 3, columns (4) and (5), the coefficients of Dei remain highly significant under the 1% statistical level, while they are much smaller than 0.8713 in Table 3, column (1). Meanwhile, the coefficients of INN and IND are positive and significant as before. That indicates innovation level and industrial upgrading play partial mediating roles in promoting IGE in a digitized economy.

Robustness checks

To verify the accuracy of the benchmark regression results, we continue to conduct the following robustness checks.

First, we adopt another approach to assess the inclusive green growth level of cities in China. Referring to Fan et al. (2022), we construct an inclusive green growth indicator system that includes the economic system, social system, and environmental system (shown in Table 7 in the Appendix). Then, we introduce the Entropy-TOPSIS method to re-evaluate inclusive green growth (IGI) in the sample cities. Based on this, we re-examine the influence of the digital economy on inclusive green growth by taking IGI as the dependent variable. The results are exhibited in Table 4, column (1). From Table 4, it is not difficult to see that the coefficient of Dei is positive and significant at the 1% level; this result is consistent with the baseline regression consequence. Meanwhile, to eliminate the estimation bias, we set the weights of the economic system, social system, and environmental system to 0.33, respectively, and recalculated the dependent variables. The regression result is shown in Table 4, column (2). It can be observed that the coefficient of Dei is positive at the 1% statistical level, which indicates the digital economy plays a vital role in promoting inclusive green growth in cities in China.

Second, to avoid the potential measure bias of the digital economy by the Entropy-TOPSIS approach, we apply the internet penetration rate (INT) as a proxy for the digital

Table 4 The estimation results of robust checks

	(1) IGI	(2) IGI	(3) IGE
Dei	3.31680*** (7.96282)	1.29930*** (0.19486)	
FD	−0.01490 (0.02518)	−0.00055 (0.00080)	0.06628** (0.02919)
FDI	0.18281*** (0.06910)	0.02263*** (0.00609)	0.24775*** (0.07271)
URB	0.64245 (0.42076)	0.01036 (0.01191)	−0.02833 (0.58099)
GI	−1.58151** (23,998.77547)	−0.79932 (1048.29349)	−1.23605*** (34,161.81946)
ED	1.82292*** (0.29531)	0.05092** (0.02270)	1.44442*** (0.28489)
INT			0.08064*** (0.01356)
_CONS	−11.67779*** (2.88351)	−0.31733*** (0.22893)	−10.76008*** (2.71823)
City fixed	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes
observations	2810.00000	2810.00000	2810.00000
R ²	0.76510	0.78897	0.71434

***, **, and * denote 1%, 5%, and 10% significance levels, respectively. Robust standard errors in parentheses

economy. Due to the Internet being the infrastructure of the digital economy, cities with more developed internet penetration rates also have a higher degree of digitization simultaneously. Thus, we take as our core independent variable, and our dependent variable is inclusive green growth efficiency assessed by the DEA model. The regression result is shown in Table 4, column (3). It could be observed that the coefficient is positive, passing the 1% significant level. This result is consistent with the baseline regression' results. This implies the robustness of the baseline regression.

By analyzing the abovementioned econometric model results, we have preliminarily verified the hypothesis proposed in the “[Theoretical framework and hypotheses](#)” section. That is, the development of the digital economy in Chinese cities can significantly enhance the level of inclusive green growth. Accelerating urban innovation and promoting industrial upgrading are the two main transmission paths that partly explain this link. However, the econometric model inevitably has some potential problems. On the one hand, cities with high levels of digital economic development may perform well in their inclusive growth, so there may be a reversal causal relationship between the dependent and independent variables. On the other hand, there may be a potential multicollinearity relationship between the

core independent and control variables, leading to errors in the estimation results. In addition, this article's core independent and dependent variables may not have a simple linear relationship. To tackle these issues, we will employ a machine learning algorithm to conduct a more in-depth empirical investigation in the next subsection and get more detailed results.

Empirical analysis based on a machine learning algorithm

We adopt Python software to implement the programming of machine learning algorithms. In this process, we treat independent variables as features. A prerequisite for constructing the machine learning model is that there is a high correlation between the individual features and the dependent variables. Therefore, we use the “seaborn toolbox” to draw a heat map of the correlation coefficients between variables, as shown in Fig. 6.

It can be observed that the correlation coefficient between our core independent variable Dei and the dependent variable, IGE, is 0.81, indicating there exists a high positive correlation between the two variables. For other control variables, FD, URB, FDI, and ED are all positively correlated with IGE, and the correlation coefficients are greater than 0.4 without exception. The correlation between these variables and IGE is obvious. It is worth noting that the correlation coefficient between GI and IGE is −0.25, indicating a negative correlation between them. In summary, these results show a reasonable correlation between the features selected in this study. There is no redundant feature that needs to be deleted.

Moreover, we apply the grid search algorithm to optimize the parameters of the machine learning model. These parameters' settings will affect the models' performance (Akbari et al. 2021). Since the three machine learning models adopted in this study are all decision tree-based algorithms, the max tree depth and the number of base learners are the parameters we focus on optimizing. Meanwhile, we use default values for other less important parameters. Generally, as the number of base learners and the maximum tree depth increase, the model's goodness of fit will increase. However, when these parameters reach a certain value, the model's goodness of fit will not continue to improve and increase the calculation workload. Therefore, these parameters should be adjusted to a reasonable range. Figure 7 shows the schematic of the machine learning model parameter adjustment.

Following this idea, we finally get the optimal parameters of RF, XGBoost, and LightGBM machine learning models, as shown in Table 5.

Then, we divide the whole dataset of 2810 samples into a training set and a testing set according to the ratio of 9:1. Among them, the training set is used to train the models,

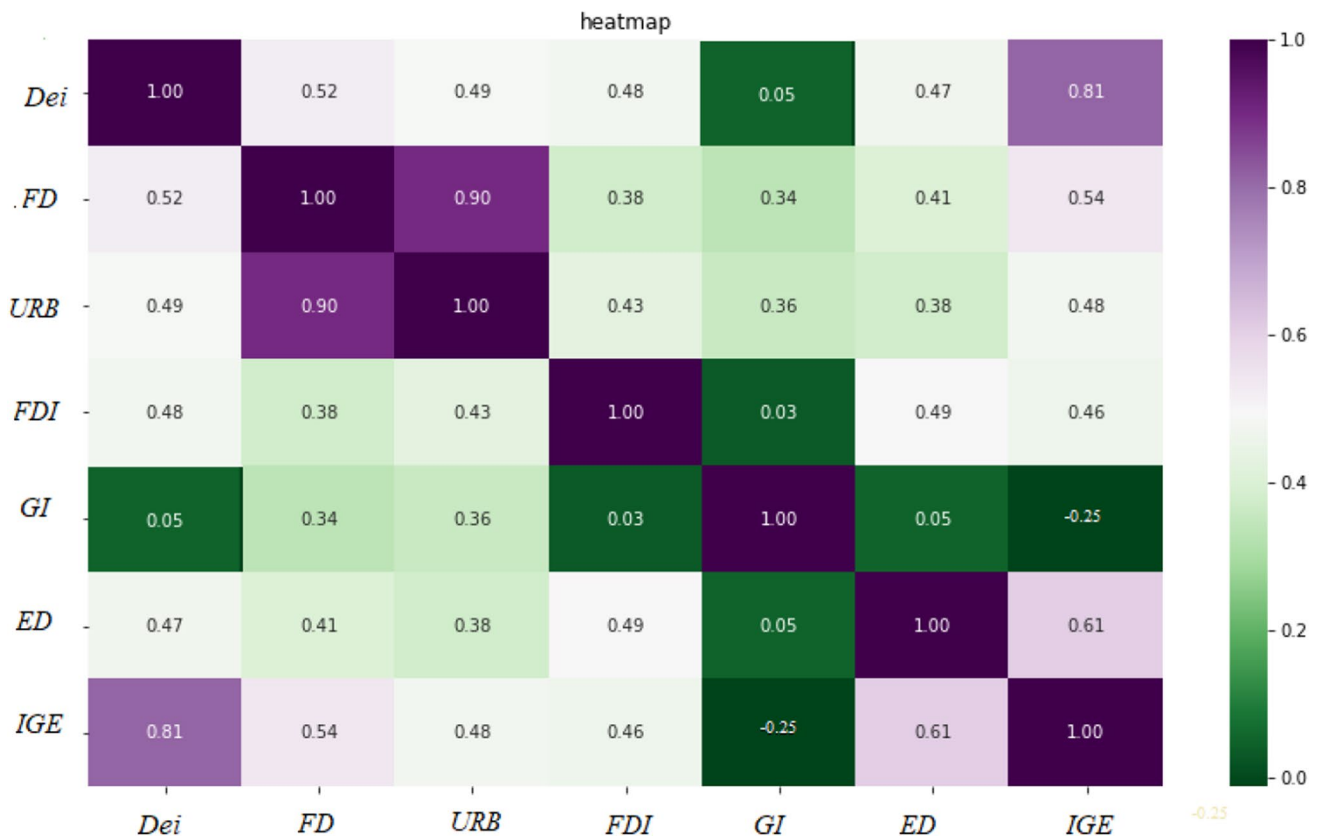


Fig. 6 The correlation coefficient heat map of the variables

while the test set is used to check the performance of the models. In the process of training samples, the machine learning models will automatically identify the intrinsic correlation between each feature variable and dependent variable. Afterward, we take the six feature variables of the whole dataset as the model’s input and use the “feature importance” command by Python software to estimate the importance weight of each feature variable. Finally, we focus on the contribution weight of the Dei to inclusive green growth. The results are shown in Fig. 8.

It can be observed from Fig. 8 that among the three machine learning models, our core independent variable of this study, the digital economic index, has the largest contribution weight to the dependent variable, exceeding 70% without exception. This indicates that digital economy development is the main engine driving cities’ inclusive green growth in China. This conclusion is highly consistent with the research of Ren et al. (2022). The study documents that digital economy agglomeration exerts a positive influence on inclusive green growth. However, their study did not introduce machine learning algorithms and did not clearly reveal the contribution weight of the digital economy in influencing inclusive green growth. For other control variables, except for the relatively high contribution weight

of economic development (ED) (about 10% ~ 13%), other variables have little impact on the inclusive green growth of cities in China. This shows that multiple potential factors driving inclusive green growth in cities in China need to be further stimulated.

Furthermore, we evaluate the performance of machine learning algorithms. Referring to existing literature, the evaluation indicators are divided into the goodness of fit (R^2) and a nest of error indicators (e.g., MSE, RMSE, MAE, and MAPE). The closer the goodness of fit to 1, the better the model performance, and the smaller the error indicators, the better the machine learning model’s performance. These indicators are shown in Table 6. Comparing the R^2 of testing set, the R^2 of three models are 0.826, 0.829, and 0.814, indicating the performance of XGBoost is the best and this algorithm is optimal. Notably, all the machine learning models’ performance is better than the traditional econometric models’, where the R^2 is merely 0.6682. That implies a nonlinear connection between the digital economy and inclusive green growth in cities in China is more reasonable than a linear relationship. The goodness of fit of the empirical results based on the optimal machine learning mode (0.829) is better than the traditional econometric model (0.668). The main reason is that machine learning

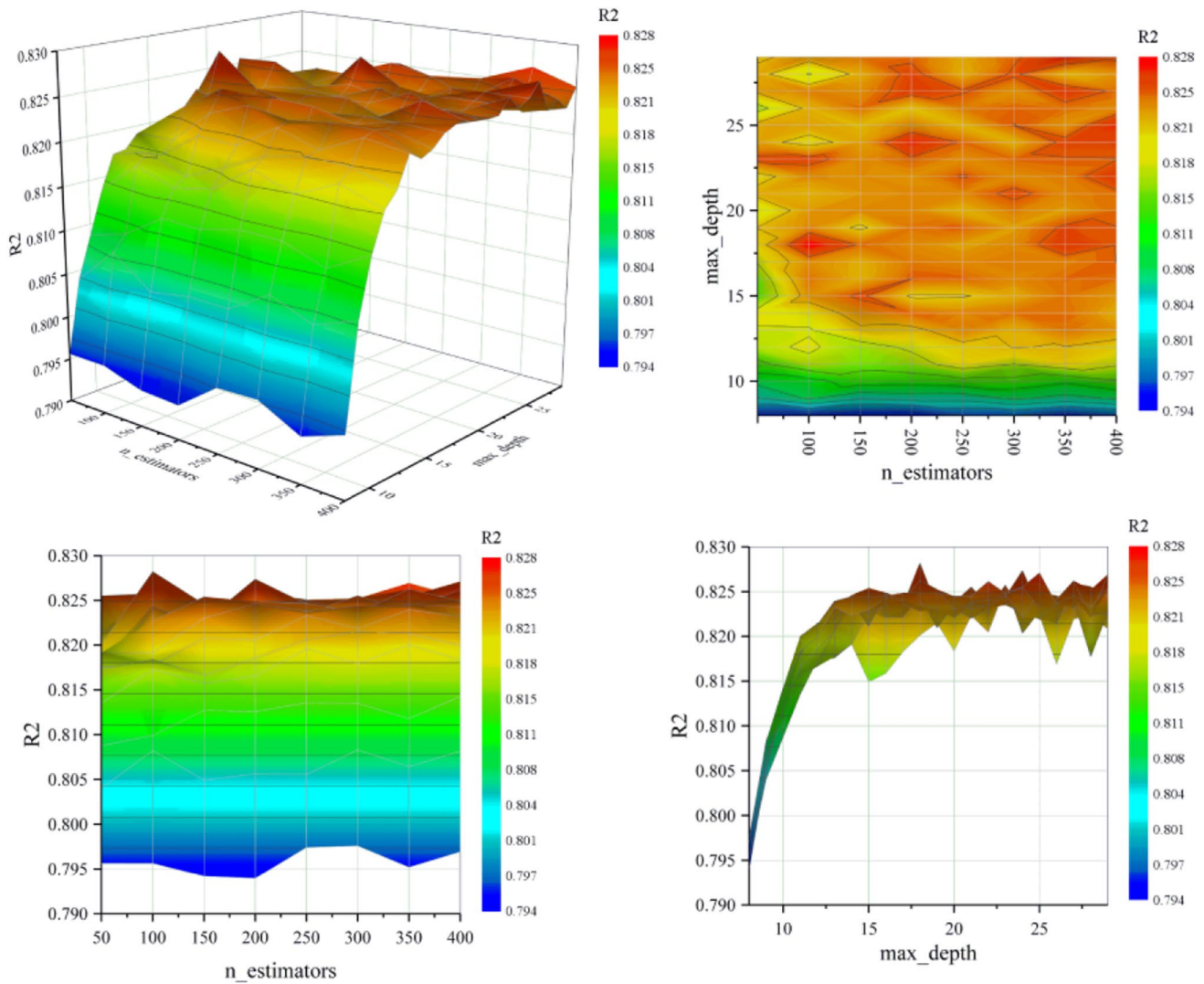


Fig. 7 Schematic of machine learning model parameter adjustment

algorithms do not presuppose a linear relationship between variables but automatically identify the relationship between independent variables and dependent variables according to training samples. Therefore, the machine learning algorithm in this study has more superior performance.

Table 5 The optimal parameters of machine learning models

Parameter	RF model	XGBoost model	LightGBM model
The number of base learners	150	130	120
Maximum tree depth	6	10	8
Minimum node splitting	2	–	–
Minimum leaf node	1	–	–
Learning rate	–	0.1	0.1
L2 regular term	–	1	1

To explore the nonlinear relationship between the digital economy and the inclusive green growth of cities in China, we use the Python software's toolbox to draw a partial dependency plot (PDP). The PDP will reveal whether the relationship between the dependent and independent variables is monotonous or more complex. This approach uses all datasets to infer their relationship and is based on the trained machine learning models. The result based on the XGBoost algorithm is shown in Fig. 9.

It can be observed that the independent and dependent variables in this study are positively correlated in general. To be specific, the DPD can be divided into two stages. In the first stage, the level of the digital economy of cities in China is within the medium level (less than or equal to 0.5), and the curve of PDP is very steep. Then, if it exceeds the threshold of 0.5, the curve becomes

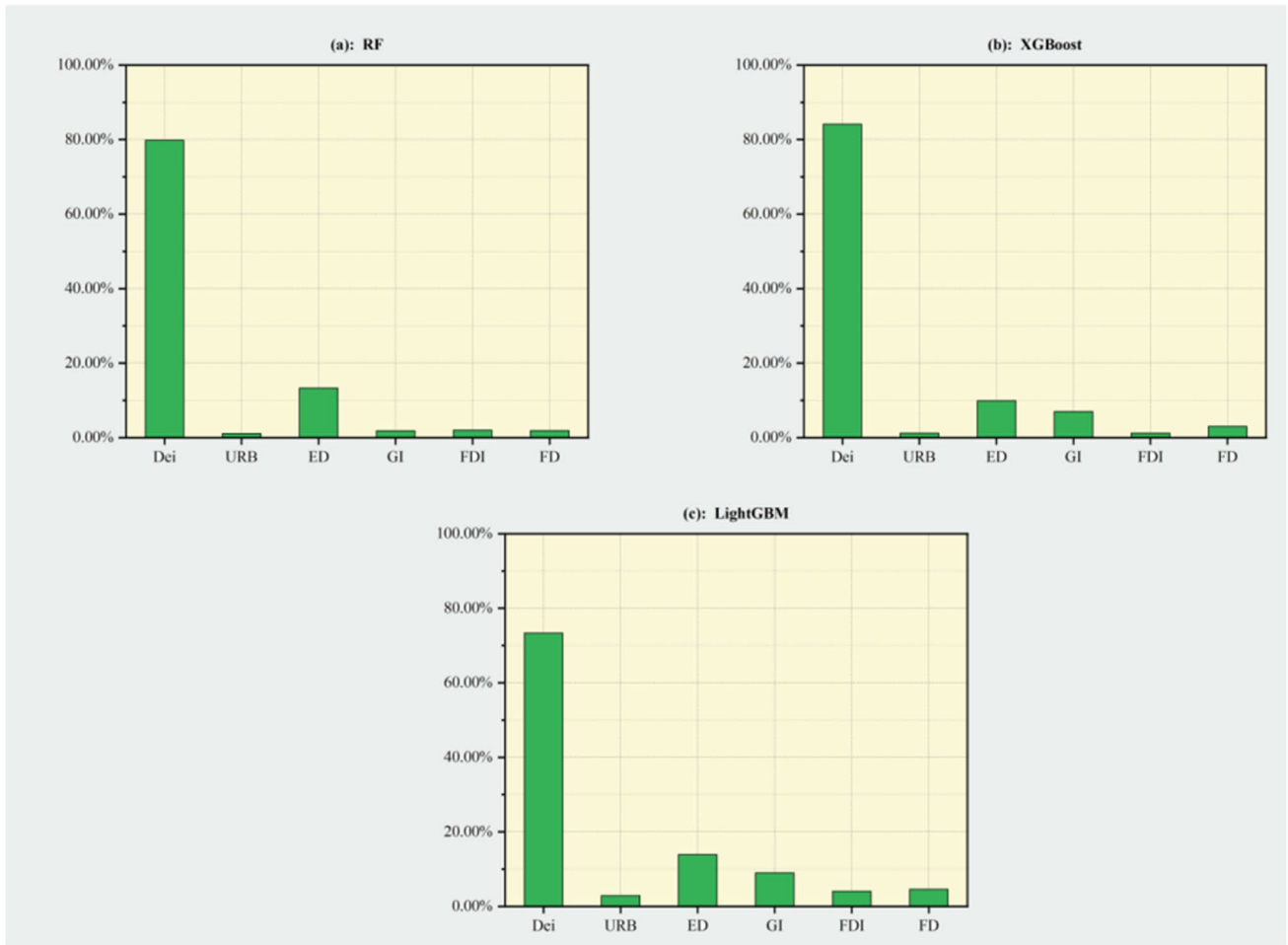


Fig. 8 Contribution weight of the feature variables

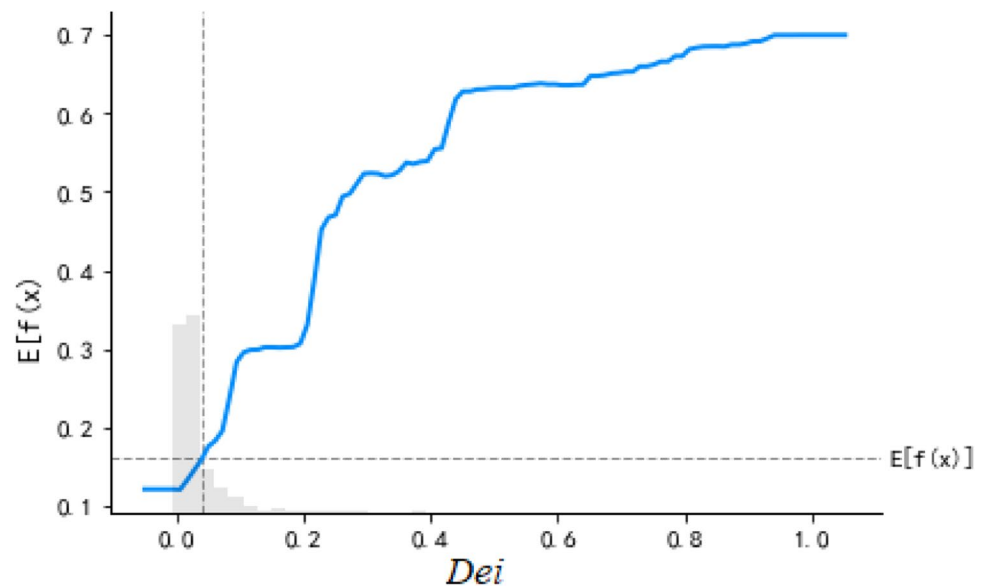
Table 6 The performance of machine learning models

Metric	RF		XGBoost		LightGBM	
	Training set	Testing set	Training set	Testing set	Training set	Testing set
R^2	0.869	0.826	0.845	0.829	0.839	0.814
MSE	0.001	0.001	0.001	0.001	0.002	0.003
RMSE	0.025	0.031	0.027	0.027	0.036	0.05
MAE	0.019	0.022	0.02	0.02	0.039	0.051
MAPE	4.96	5.776	5.259	5.485	5.843	6.527

relatively flat. This implies that the impact of digital economy development on inclusive green growth in cities in China exerts a decreasing marginal effect. China is a population superpower, and it is easier for the digital economy to exert the effect of increasing returns to scale in China. As the digital economy integrates more closely with industries and penetrates more broadly into economic activities, its positive impact on social and environmental systems will accelerate. On the one hand, a high-level digital economy means that industries have

bought into technology-driven and innovation-driven growth, changed the extensive growth model, and reduced the cost of capacity and the discharge of environmental pollutants (Asongu et al. 2018). On the one hand, the widespread popularity of the digital economy means that the digital gap between regions is bridged, and residents in different areas have the opportunity to get better access to education and health care, thus narrowing the income gap and making society more inclusive.

Fig. 9 The PDP between the digital economy and inclusive green growth of cities in China



Heterogeneity analysis

The impact of the digital economy on the inclusive green growth of cities in China has been confirmed in the previous section. In this section, we further conduct the heterogeneity analysis to explore the different impacts in different regions and the different sizes of cities, as well as the different marketization levels of cities in China.

Different regions in China

To investigate the heterogeneity of inclusive green growth in China's digital economy in cities in different geographical locations, we divided all samples into two categories: cities in the eastern region and cities in the central and western regions. This classification is mainly based on the division of the National Bureau of Statistics of China, which has been widely used in many related articles (Ren et al. 2022; Fan and Liu 2022). Theoretically, the economy of the eastern region is relatively developed, while that of the central and western regions is relatively backward. Therefore, this classification standard also follows the development level of China's economy.

As displayed in Fig. 10, the contribution weight of the digital economy to inclusive green growth has the biggest proportion among all variables in each region of China. However, with careful observation, there are some subtle differences. The contribution weight in the eastern region is 0.68, followed by the western region and the central region at 0.61 and 0.60, respectively, indicating that the digital economy plays a major role in promoting inclusive green growth in cities in the eastern region of China.

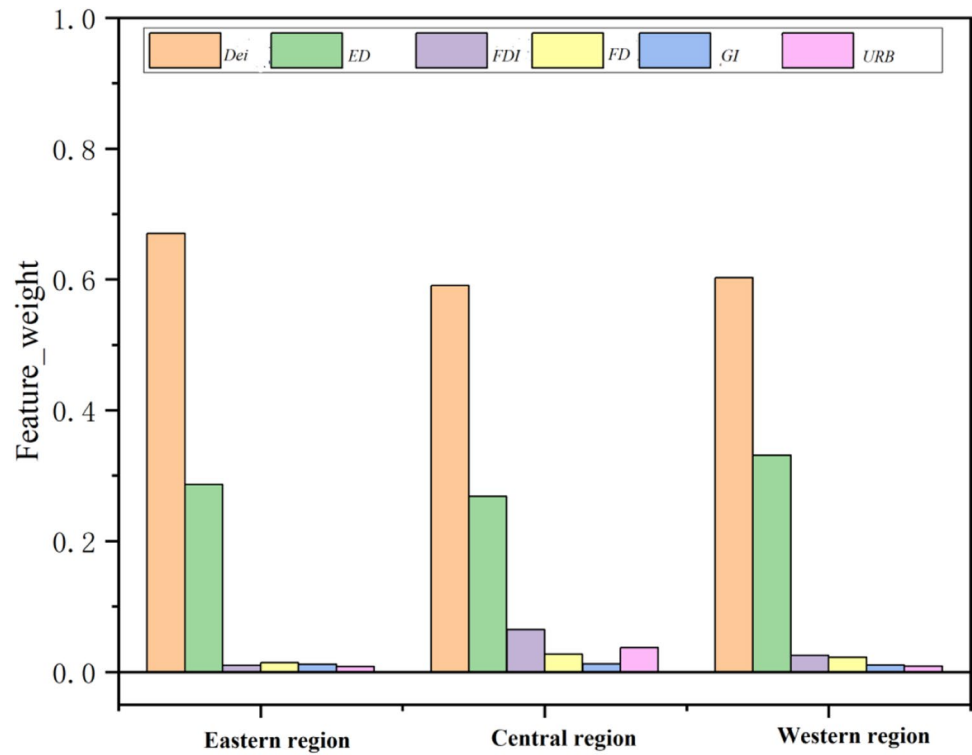
The possible reason is that the eastern region of China has good geographical advantages, an excellent economic foundation, and a relatively complete digital infrastructure. It is also the birthplace of China's digital economy. The headquarters of many digital giants are located in the eastern region of China. Thus, the digital economy exerts a more positive impact on promoting inclusive green growth in that region. However, in the central and western regions, the digital economy's contribution can not be underestimated. The digital economy has geographic penetration power and lower transaction costs, benefiting extremely remote areas in China's central and eastern regions.

Cities of different sizes in China

Meanwhile, to explore whether the digital economy has different impacts on inclusive green growth in cities with different population sizes, we divide the sample into three categories according to population size: large cities, medium cities, and small cities. This classification is based on the urban population quantile in statistics. Cities with a population of more than 66% of the quantile are large cities; less than 33% of the quantile are small cities, and in between are medium-sized cities. The result is shown in Fig. 11.

It is worth noting that the contribution weight of the digital economy to promoting inclusive green growth in large- and medium-sized cities is about 0.6. While in small-sized cities, the contribution weight is significantly lower, less than 0.1. This shows that digital finance in China significantly

Fig. 10 Heterogeneity analysis of different regions in China



promotes inclusive green growth in large- and medium-sized cities. But in smaller cities, economic development is the main engine for inclusive green growth. The possible reason

is that achieving an inclusive green growth path requires multiple factors to work together. Large- and medium-sized cities have a high degree of digitalization, a large influx of

Fig. 11 Heterogeneity analysis_ different city size

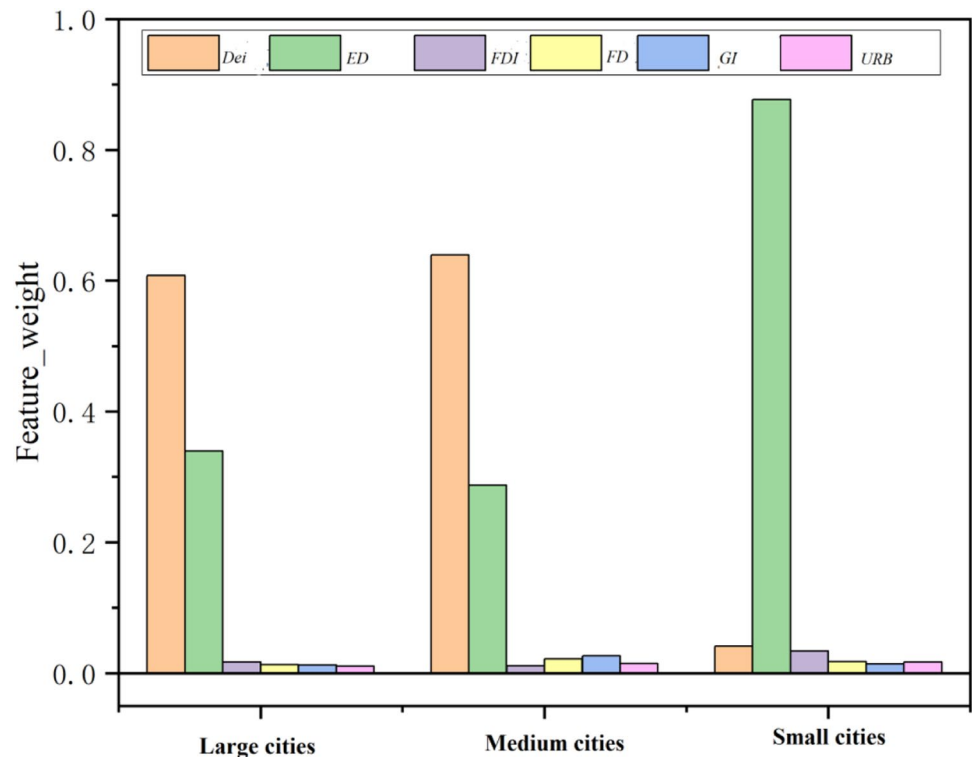
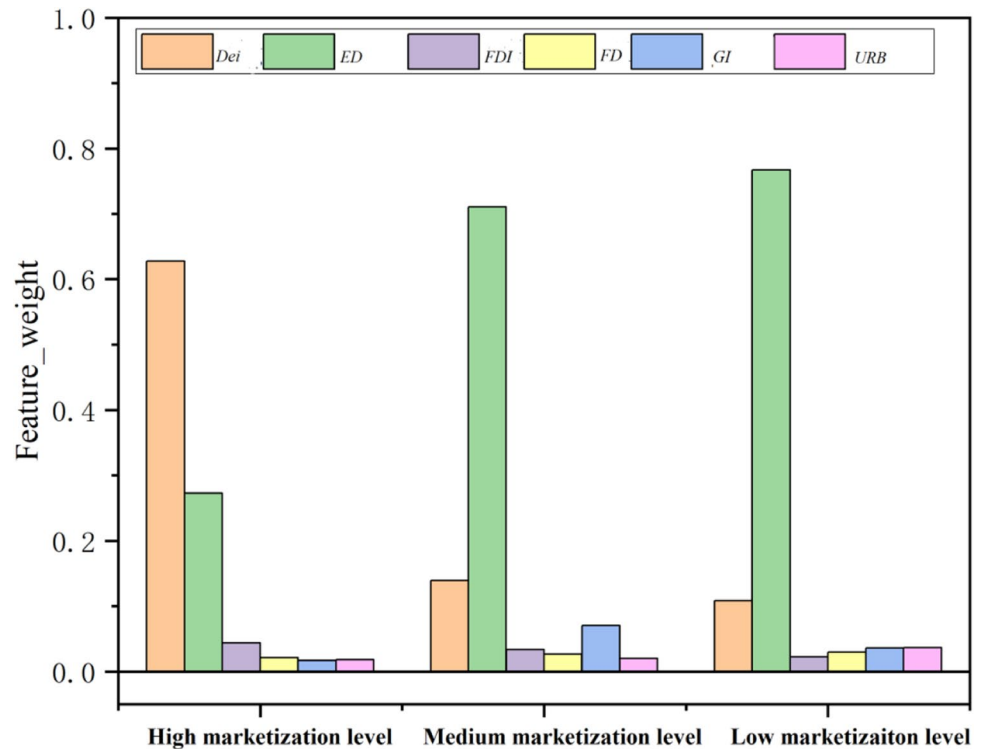


Fig. 12 Heterogeneity analysis_ marketization level



talent, and strong policies. Under the background of various resources and factors, the digital economy has greatly promoted the inclusive green growth of cities. However, small cities have weak resource-gathering abilities. Problems such as insufficient human capital and untimely policy measures restrict the development of the digital economy. For small cities, stimulating local economic vitality is the first problem to be solved.

Different marketization levels of cities

Marketization or a market-oriented economic system means that the allocation of resources mainly depends on the market rather than the government. By reducing government intervention, economic behaviors such as production, distribution, exchange, and consumption are carried out based on the market mechanism. Theoretically, higher levels of marketization mean market efficiency in the regions, which could affect the digital economy's role in promoting cities' inclusive green growth. First, we calculate the proportion of the output value of non-state-owned enterprises in cities to the total output value to represent the degree of marketization. On this basis, by using different quantiles, all samples are divided into three categories: high marketization level, medium marketization level, and local marketization level. Then, we investigate the contribution weight of the digital economy to inclusive green growth in different types of cities, and the results are shown in Fig. 12.

We can observe that in cities with high marketization levels, the contribution weight of the digital economy to inclusive green growth is greater than 0.6. However, in cities with medium and low marketization levels, its contribution weight is minimal, about 10%. This implies that the positive impact of the digital economy on inclusive green growth mainly exists in cities with high marketization levels. Economic development is the dominant factor in promoting inclusive green growth in cities with medium and low marketization.

The possible reason behind this phenomenon is that the cities with a high level of marketization in China are mainly located in the southeast coastal areas. These areas have high resource allocation efficiency and strong support for the digital industry. Meanwhile, some other policies to promote inclusive green growth in these areas are easy to form a joint force with the digital economy. For example, many cities in Zhejiang province in this region have launched initiatives such as the “common prosperity demonstration zone” and the “lucid waters and lush mountains are invaluable assets demonstration zone,” which play a synergistic role with the digital economy in promoting inclusive green growth. However, in cities with medium and lower levels of marketization, the government plays a leading role in the economic operation. Moreover, under the “local GDP tournament” pressure, these cities focus on increasing the total amount and speed of economic growth. Thus, too extensive growth

often ignores the coordination and unity of economic, social, and environmental systems. Therefore, the influence of the digital economy on inclusive green growth in these cities is minimal.

Conclusions and policy implications

As the most populous superpower in the world, China has witnessed rapid development in the digital economy in terms of the increasing number of mobile phone and Internet users in recent years. Meanwhile, China's social income gap and ecological pollution problems are also extremely serious, and implementing the inclusive green growth initiative is urgent for China. Therefore, a question will naturally arouse the attention of scholars: Does the digital economy matter for inclusive green growth? To answer this question, we investigate the impact of the digital economy on the inclusive green growth of cities in China. Specifically, we investigate the overall effect and transmission mechanism of the digital economy on inclusive green growth efficiency in a sample of 281 cities in China over 2011 ~ 2020. Results from the panel data indicate that digital economy development significantly and positively affects inclusive green growth. Furthermore, the digital economy enhances inclusive green growth mainly by driving innovation and promoting industrial upgrading. We also complement our analysis by using machine learning algorithms to explore the nonlinear connection between the digital economy and inclusive green growth. We also calibrate the contribution weight of the digital economy among all the drivers of inclusive green growth. The results show that the impact of digital economy development on inclusive green growth in cities in China exerts a decreasing marginal effect. Furthermore, the heterogeneity test results show that the digital economy's contribution to inclusive green growth is prominent in large cities, cities in central China, and cities with a high degree of marketization. Overall, this study has shown that there exists a positive association between the digital economy and inclusive green growth in China. This evidence will help governments in China and developing countries like China formulate policies that scientifically promote the digital economy to drive inclusive green growth.

From a policy perspective, the following measures should be considered in order to achieve the inclusive

green growth goal. First of all, the government should vigorously promote the wide penetration of digital technology in various industries. Therefore, it is necessary to promote digital infrastructure construction throughout the country, such as optical fiber and 5G network coverage. Empowering cities with digital technology makes smart cities blossom everywhere in China. In addition, relying on digital technology to seek the transformation and upgrading of traditional low-value-added industries and promote the breeding of high-value-added and innovation-driven industries can promote economic growth while making society more inclusive and the environment greener. Second, city governments should implement measures to develop the digital economy, for example, by attracting advanced scientific and technological talents to settle in their cities and improving the digital literacy of local residents through training. Furthermore, legislation on the digital economy should be strengthened to guide the digital economy to support the real economy without generating speculative bubbles. Also, rewarding enterprises and individuals who have made outstanding contributions in promoting the digital transformation of cities. In addition, triggering the research results of universities and scientific research institutions on the digital economy will boost the digital transformation of local enterprises. Thirdly, policymakers in small and low-marketization cities should promote the development of inclusive green growth solutions by bridging the digital divide. It should actively leverage the advantages of the digital economy, such as low transaction costs and the scale effect, to promote inclusive green growth. Finally, campaigns to increase public awareness of the benefits associated with the influence of digital economy development and inclusive green growth could be promoted.

Limited by data acquisition and research level, this study inevitably has some limitations. One of the limitations of this study is that the conclusions and policy implications apply at the overall level and do not consider each city. In fact, there are some differences in the development pattern of the digital economy in China's cities. Therefore, it is essential to extend this study to a specific city level to get further insights into the impact of these policies. Future studies could also extend this work by identifying additional transmission channels, particularly contextual ones, through which the digital economy affects inclusive green growth.

Appendix

Table 7 Evaluation index system of inclusive green growth in China

Dimension	Sub-dimension	Sub-classification	Index	Unit
Economic	Economic growth	Economic output	X1 Per capita GDP	Yuan/person
		Growth rate	X2 Annual GDP growth rate	%
		Growth potential	X3 Investment in fixed assets	Ten thousand yuan
	Income distribution	Rural income	X4 rural per capita net income	Yuan/person
		Urban income	X5 Per capita disposable income of urban residents	Yuan/person
		Urban economic resilience	X6 Economic resilience index	/
		Urban–rural income gap	X7 Per capita income ratio of urban and rural residents	Multiple
Social	Fairness of opportunities	Educational opportunities	X8 Ratio of students in primary schools	%
			X9 Ratio of students in Middle schools	%
		Employment opportunities	X10 Employment ratio excludes the primary industry	%
	X11 urban unemployment rate		%	
	Medical opportunities	X12 Number of health technicians	Per thousand population	
		X13 Number of medical institutions	Per thousand population	
	Social security opportunities	X14 Basic old-age people insurance	%	
		X15 Basic medical insurance	%	
	Infrastructure opportunities	X16 Telecommunications and Post income per capital	yuan	
		X17 Passenger volume per population	Per people	
X18 Freight volume per population		Ton		
X19 Internet coverage		%		
Environment		Green development	Green production	X20 Industrial wastewater discharge per GDP
	X21 Sulfur dioxide discharge per GDP			Tton/ten thousand yuan
	X22 Industrial dust discharge per GDP			Ton/ten thousand yuan
	Green consumption	X23 Carbon dioxide discharge per GDP	tTon/ten thousand yuan	
		X24 Energy consumption per capita	Ton	
	Environmental governance	X25 Utilization rate of general industrial solid waste	%	
		X26 Sewage disposal rate	%	
		X27 Harmless rate of domestic garbage	%	

Acknowledgements The authors are grateful to the editor and anonymous reviewers for their insightful and helpful comments.

Author contribution Chunhua Xin: Conceptualization, Writing-review & editing, Methodology, Software, Formal analysis. Shuangshuang Fan: Conceptualization, Writing-review & editing, Methodology, Software, Formal analysis, Validation. William Mbanye: Writing-review & editing, Formal analysis, Validation. Muhammad Shahbaz: Writing-original draft, Writing-review & editing, Formal analysis.

Funding This work was funded by the Beijing Natural Science Foundation (grant no. 9222026).

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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