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Research article

What role does digital finance play in low-carbon development? Evidence from five major urban agglomerations in China

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ABSTRACT

In the epoch of the digital economy, digital finance (DF) has become an indispensable engine driving the high-quality development of the Chinese economy. The issues of how DF can be used to alleviate environmental pressure and how a long-term governance mechanism for carbon emissions reduction be formed have become particularly important. Based on the panel data of five national urban agglomerations in China from 2011 to 2020, this study utilizes the panel double fixed-effects model and chain mediation model to verify the impact mechanism of DF on carbon emissions efficiency (CEE). Some valuable findings are drawn below. First, the overall CEE of the urban agglomerations has potential for improvement, and the CEE and DF development level of each urban agglomeration have regional heterogeneity. Second, a U-shaped correlation is observed between DF and CEE. Technological innovation and industrial structure upgrading have a chain mediating effect in DF affecting CEE. In addition, the breadth and depth of DF have a notable negative impact on CEE, and the digitalization degree of DF shows a significant positive correlation with CEE. Third, the influencing factors of CEE have regional heterogeneity. Finally, this study provides relevant suggestions based on the empirical conclusions and analysis.

Credit author statement

Jie Wu: Conceptualization, Formal analysis, Investigation, and Writing – original draft. **Ruizeng Zhao**: Methodology, Data curation, Formal analysis, Writing - review & editing. **Jiasen Sun**: Investigation, Supervision, Writing - review & editing.

1. Introduction

In recent years, global CO_2 emissions increased sharply, leading to rising temperatures and frequent natural disasters, which have seriously affected human life and sustainable development (Koondhar et al., 2021). The promotion of industrialization and urbanization in China led to rapid economic growth but also increased fossil energy consumption, thereby further aggravating environmental pressure on China (Guilhot, 2022). As the world's largest energy consumer and CO_2 emitter (Hou et al., 2021), China's annual coal and oil consumption accounts for 70% of its total energy consumption, and its CO_2 emissions account for 36.65% of global CO_2 emissions in 2020. With the international community continuing to pay attention to climate change, China has committed to low-carbon development and issued a series of policies to strengthen environmental governance (Song et al., 2020). In 2020, China voluntarily proposed a dual carbon goal, that is, to strive to peak carbon emissions by 2030 and achieve carbon neutrality by 2060.

As the core of the modern economy, the financial industry shoulders the heavy responsibility of energy conservation and emission reduction while promoting high-quality economic development (Shahbaz et al., 2016). With the integration of digital technology in the financial industry, digital finance (DF) has emerged. The green emission reduction effect of DF has gradually attracted the attention of scholars. Existing research focuses mainly on the relationship between DF and carbon emissions. For instance, Lee et al. (2022) analyzed the nonlinear relationship between DF and carbon intensity, and concluded that financial digitization could reduce carbon intensity. Wang et al. (2022) explored the spatial effect of DF on CO_2 emissions and found that industrial structure and economic level have a mediating effect. Zhang et al. (2023) found that DF can increase consumption-based embodied carbon emissions by changing the consumption structure and consumption level.

To the best of our knowledge, a few studies have explored the

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relationship between DF and carbon emission efficiency (CEE). For example, Zhang and Liu (2022) examined the impact of DF on China's CEE from a spatial perspective and analyzed the mediating role of green technology innovation. Apart from Zhang and Liu (2022), the specific mechanism of DF affecting CEE needs to be further explored.

To fill this research vacancy, this study investigates the internal transmission pathways between DF and CEE and evaluates the emissions reduction effect of DF in China. This study takes China's Yangtze River Delta Urban Agglomeration (YRDUA), Pearl River Delta Urban Agglomeration (PRDUA), Beijing−Tianjin−Hebei Urban Agglomeration (BTHUA), Yangtze River Middle-reach Urban Agglomeration (YRMUA), and Chengdu−Chongqing Economic Circle (CCEC) as samples to identify the effect and impact path of DF on CEE. The specific issues include the following: (1) Does DF have an emissions reduction effect? (2) How does DF affect CEE? (3) Whether heterogeneous characteristics exist?

To answer the questions above, first, this study constructs an extended stochastic impacts by regression on population, affluence, and technology (STIRPAT) panel double fixed-effects model to explore the emissions reduction effect of DF. Second, this study analyzes the impact mechanism of DF on CEE by constructing multiple mediation and chain mediation models. Third, this study further explores the nonlinear relationship between DF and CEE and their heterogeneity characteristics. Finally, this study proposes relevant policy recommendations for improving CEE in China.

The contributions of this study are as follows: First, discussions on the effect of DF on emissions reduction in urban agglomerations are lacking; thus, this study fills the research gap. Second, previous studies on the mediating effect of CEE focused mainly on testing a single mediator variable. To the best of our knowledge, scholars have yet to explore whether technological innovation and industrial structure upgrading exist chain relationship on the path of DF affecting CEE. This study verifies the complex path of DF's effect on CEE from an empirical perspective. Third, based on the robust research conclusions, this study presents constructive proposals for improving the CEE of urban agglomerations through DF.

The rest of this paper is organized as follows: Section 2 theoretically analyzes the impact mechanism of DF on CEE and proposes the research hypotheses. Section 3 describes the study design in detail, and Section 4 verifies the mechanism and impact of DF on CEE and conducts robustness tests. Finally, Section 5 refines the conclusions and presents targeted recommendations.

2. Impact mechanism of DF on CEE

2.1. Direct impact of DF on CEE

Scholars generally agree that DF has an abatement effect, but some hold opposing views. Wang and Guo (2022) found that DF could help companies in the green sector raise funds quickly, alleviate distortions in their corporate capital allocation, promote corporate transformation and upgrading, and accelerate the achievement of strategic goals for sustainable development. Demertzis et al. (2018) concluded that financial institutions can accurately identify whether enterprises have green and low-carbon characteristics through digital technology, which can increase the financing efficiency of environment-friendly corporations and relieve environmental pressure. Zhang and Liu (2022) assessed the impact of DF on the CEE of 283 cities in China and indicated that the collaborative effect of DF and green technology can significantly increase CEE.

However, DF development may also enlarge CO_2 emissions and reduce CEE. Wang and Guo (2022) found that DF significantly increased the CO_2 emissions of cities in Central China. Zhao et al. (2021) observed that manufacturing and industrial enterprises that obtain financing through digital financial products increase their energy consumption, which further increases their CO_2 emissions and reduces their CEE. Based on the above analysis, this study proposes Hypothesis 1:

H1. DF can promote (or inhibit) the improvement of CEE.

2.2. Mediating effect of technological innovation and industrial structure upgrading

Technological innovation and industrial structure upgrading inject vitality into low-carbon economy development and contribute positively to CO_2 emissions reduction. As a technology-driven financial innovation in the background of the Fourth Industrial Revolution, DF plays a vital role in facilitating technological innovation and industrial structure upgrading (Wang et al., 2022).

On the one hand, the technological effect of DF is reflected mainly in its ability to stimulate corporate technological innovation, especially green technology innovation. That is, DF can stimulate the sustainable development of green enterprises to decrease CO_2 emissions and increase CEE (Wu and Huang, 2022). The long period and high risk of technology R&D make traditional finance unwilling to serve small and medium-sized enterprises (SMEs). Compared with the credit discrimination of traditional finance, DF lowers the credit threshold, broadens financing channels, provides financing solutions for the technological innovation of SMEs. Cao et al. (2021) concluded that DF could overcome the financing problem of technological innovation and strengthen its spillover effect. The authors also revealed that DF can significantly enhance the performance of the energy environment through green technology innovation. Zhang and Liu (2022) determined that DF can guide capital into green technology R&D, thereby solving the financing dilemma of green technology development and improving CEE.

On the other hand, DF can provide financial support to industries to promote industrial structure upgrading. An advanced and rationalized industrial structure can weaken environmental degradation and reduce CO_2 emissions in the production activities of the industrial sector, which are conducive to improving CEE. Wan et al. (2022) investigated the mediating role of industrial structure in the transmission mechanism through a mediation model and revealed that DF can indirectly alleviate pollution emissions through the industrial structure.

In addition, technological innovation plays an essential function in encouraging long-term stable economic growth and acts as a key to speeding up the transformation of the traditional economy into a low-carbon economy. Technological innovation can also promote industrial structure upgrading; thus, their relationship should be considered. With the system generalized method of moments, Wang and Wang (2021) concluded that financial development can significantly promote industrial structure upgrading in China, with technological innovation playing an intermediary role. Therefore, DF may also promote industrial structure upgrading through technological innovation, thereby indirectly affecting CEE. Based on the above analysis, this study proposes the three following hypotheses:

H2. DF can indirectly affect CEE by promoting technological innovation.

H3. DF can indirectly affect CEE by promoting industrial structure upgrading.

H4. DF drives industrial structure upgrading by promoting technological innovation, thereby indirectly affecting CEE.

The core concepts of the above four hypotheses are shown in Fig. 1.

3. Methodology and variables

3.1. Model

3.1.1. Super-efficiency slacks-based measure model with undesirable output

Due to the strong discriminative ability and consideration of undesirable outputs (Tone, 2002; Yu et al., 2019), this study used the super-efficiency slacks-based measure (S-SBM) model with undesirable output to calculate CEE. This study assumes that n DMUs exist, and each

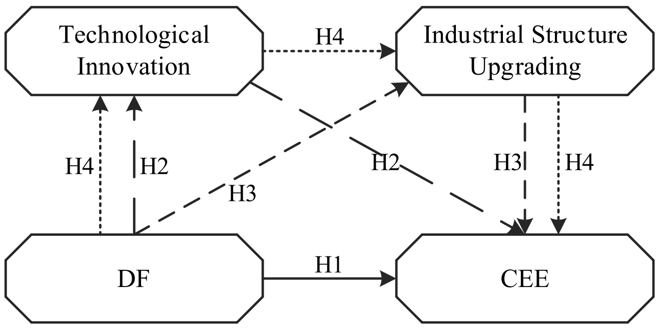

Fig. 1. Influence mechanism.

$DMU_j (j = 1, 2, \cdots, n)$ uses i inputs to produce r desirable outputs and z undesirable outputs. $X_j = [x_{1j}, x_{2j}, \cdots, x_{ij}] \in R^i_+$, $Y_j = [y_{1j}, y_{2j}, \cdots, y_{rj}] \in R^r_+$, and $B_j = [b_{1j}, b_{2j}, \cdots, b_{zj}] \in R^z_+$ represent the matrices of the inputs, desirable outputs, and undesirable outputs, respectively. The S-SBM model is as follows:

$$
\begin{aligned}
&E = \min \frac{1 + \frac{1}{l}\sum_{i=1}^{l} \frac{s_i^-}{x_{ik}^g}}{1 - \frac{1}{q+p}\left(\sum_{r=1}^{q} \frac{s_r^+}{y_{rk}} + \sum_{z=1}^{p} \frac{s_z^{b-}}{b_{zk}}\right)} \\
&s.t. \\
&\sum_{j=1,\neq k}^{n} \lambda_j x_{ij} - s_i^- \leq x_{ik} \ , \ i = 1, \ldots, l; \\
&\sum_{j=1,\neq k}^{n} \lambda_j y_{rj} + s_r^+ \geq y_{rk} \ , \ r = 1, \ldots, q; \\
&\sum_{j=1,\neq k}^{n} \lambda_j b_{zj} - s_z^{b-} \leq b_{zk} \ , \ z = 1, \ldots, p; \\
&1 - \frac{1}{q+p}\left(\sum_{r=1}^{q} \frac{s_r^+}{y_{rk}} + \sum_{z=1}^{p} \frac{s_z^{b-}}{b_{zk}}\right) > 0; \\
&\lambda \geq 0, s^- \geq 0, s^+ \geq 0, s^{b-} \geq 0.
\end{aligned}
\tag{1}
$$

In Equation (1), x_{ij}, y_{rj}, and b_{zj} represent the i-th input, r-th desirable output, and z-th undesirable output of the DMU_j, respectively; s_i^-, s_r^+, and s_z^{b-} represent the slack variables of the input, desirable output, and undesirable output, respectively; λ_j is the intensity vector; and E is the CEE value that must be obtained. Moreover, $E \geq 1$ indicates that the DMU is efficient, whereas $E < 1$ indicates that the DMU is inefficient.

3.1.2. Benchmark model

The STIRPAT model can overcome the inadequate assumptions of the IPAT model (York et al., 2003), which can be further expanded and decomposed according to reality (Vélez-Henao et al., 2019). Therefore, the STIRPAT model is highly suitable for examining the relationship between environmental pressure and population, affluence, and technology. Its general form is as follows:

$$I = aP^bA^cT^de \tag{2}$$

In Equation (2), I represents CEE, P represents the population scale, A represents the economic level, and T represents the technological level. In addition, a represents the intercept term; b, c, and d represent the elastic coefficient of P, A, and T, respectively; and e is the error term. Equation (2) can be converted into a linear expression after logarithmic processing, which can eliminate the time series fluctuation trend and overcome the heteroskedasticity of the series. The transformed version is shown in Equation (3).

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \tag{3}$$

After the control variables are introduced, Equation (3) can be extended to Equation (4).

$$\ln CEE_{it} = \alpha + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{4}$$

In Equation (4), i and t represent the observation sample and time, X_{it} represents the control variables, μ_i denotes the individual effect, v_t means the time effect, and ε_{it} represents the error term. To explore the direct impact of DF on CEE, the *DF* is added to Equation (4) to construct the benchmark model, as shown in Equation (5).

$$\ln CEE_{it} = \alpha + \delta \ln DF_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{5}$$

Three subdimension indicators are used to replace *DF* in Equation (5) to explore the differences in the impact of the coverage breadth (*DF_bre*), usage depth (*DF_dep*), and digitization degree (*DF_dig*) of DF on CEE.

3.1.3. Mediation model

This study first constructs a multiple mediation model for technological innovation (*TI*) and industrial structure upgrading (*Ins*) before building a chain mediation model. To verify H2 and H3, Equations (6)–(8) are constructed based on Equation (5), as follows:

$$\ln RD_{it} = \alpha + \varphi \ln DF_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it}, \tag{6}$$

$$\ln Ins_{it} = \alpha + \rho \ln DF_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it}, \tag{7}$$

$$\ln CEE_{it} = \alpha + \delta' \ln DF_{it} + \varphi' \ln TI_{it} + \rho' \ln Ins_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it}. \tag{8}$$

The multiple mediation model constructed by Equations (5)–(8) can jointly test whether *TI* and *Ins* have mediating effects on the path of DF affecting CEE. Moreover, δ' is the direct effect of DF on CEE, $\varphi\varphi'$ is the mediating effect of *TI*, $\rho\rho'$ is the mediating effect of *Ins*, δ is the total effect, and $\delta = \delta' + \varphi\varphi' + \rho\rho'$. If δ' is significant at the 5% significance level, then the model will have a partial mediating effect; otherwise, it will have a complete mediating effect.

A chain mediation model including Equations (5), (6), (8) and (9) is constructed to verify H4.

$$\ln Ins_{it} = \alpha + \rho \ln DF_{it} + \lambda \ln TI_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{9}$$

In Equations (5), (6), (8) and (9), δ represents the total effect, δ' represents the direct effect, $\varphi\varphi'$ represents the mediating effect of *TI*, and $\rho\rho'$ represents the mediating effect of *Ins*. In addition, $\varphi\lambda\rho'$ represents the chain mediating effect of *TI* and *Ins*, $\varphi\varphi' + \rho\rho' + \varphi\lambda\rho'$ represents the total indirect effect, and $\delta = \delta' + \varphi\varphi' + \rho\rho' + \varphi\lambda\rho'$.

3.1.4. Nonlinear model

So far as we know, no research has been conducted on the nonlinear relationship between DF and CEE. To further understand the impact mechanism of DF on CEE, this study adds the quadratic term of DF to Equations (5) and (8).

$$\ln CEE_{it} = \alpha + \delta \ln DF_{it} + \delta' (\ln Dif_{it})^2 + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it}, \tag{10}$$

$$\ln CEE_{it} = \alpha + \delta \ln DF_{it} + \delta' (\ln DF_{it})^2 + \varphi \ln TI_{it} + \rho \ln Ins_{it} + \beta \ln X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{11}$$

When δ and δ' in Equations (10) and (11) are statistically significant and have different signs, a nonlinear relationship will exist between DF and CEE. If $\delta < 0$ and $\delta' > 0$, then a U-shaped relationship will exist between DF and CEE. If $\delta > 0$ and $\delta' < 0$, then an inverted U-shaped relationship will exist.

3.2. Variables

3.2.1. Explained variable

As the explained variable, *CEE* is measured mainly by Model (1). The input indicators include (1) energy consumption (*Enc*; 10,000 tons of standard coal), (2) employment (*Emp*; 10,000 people), and (3) capital stock (*Cas*; RMB 100 million). The capital stock is calculated according to the perpetual inventory method, in which the depreciation rate is 10.96%, and the base period is 2000 (Guo et al., 2022). The desirable output is gross domestic product (*GDP*; RMB 100 million). The undesirable output is CO_2 emissions (CO_2; 10,000 tons), derived from an open-source dataset deduced by Oda et al. (2018). The other data are from the *statistical yearbooks* of the various cities.

3.2.2. Core explanatory variable

In this study, DF is the core explanatory variable. This study takes the digital financial inclusion index as a proxy for *DF*, which is obtained from Guo et al. (2020). The digital financial inclusion index covers three subdimensions: *DF_bre*, *DF_dep*, and *DF_dig*. This study investigates the effects of the different dimensional subindicators on CEE in various urban agglomeration cities.

3.2.3. Mediator variables

This study sets two mediator variables: *TI* and *Ins*. *TI* uses R&D expenditures as a proxy variable. According to the Petty–Clark theorem, as the economy grows, the industrial structure will change accordingly, and the industry focus will shift gradually from the primary industry to the secondary industry then to the tertiary industry (Ding et al., 2020). In this study, the proportion of the primary industry, secondary industry, and tertiary industry in the GDP is taken as the components of the spatial vector, that is, $X_0 = (x_{1,0}, x_{2,0}, x_{3,0})$. Next, angles θ_1, θ_2, and θ_3 are calculated by Equation (12) based on the vectors of X_0, $X_1 = (1,0,0)$, $X_2 = (0,1,0)$, and $X_3 = (0,0,1)$.

$$\theta_j = \arccos\left(\frac{\sum_{i=1}^{3} x_{i,j} * x_{i,0}}{\left(\sum_{i=1}^{3}\left(x_{i,j}^2\right)^{1/2} * \sum_{i=1}^{3}\left(x_{i,0}^2\right)^{1/2}\right)}\right), j = 1,2,3. \tag{12}$$

Finally, the *Ins* index can be calculated by Equation (13).

$$W = \sum_{k=1}^{3}\sum_{j=1}^{k}\theta_j, \tag{13}$$

where the larger the W, the higher the advanced level of the industrial structure. The raw data come from the *China City Statistical Yearbook*.

3.2.4. Control variables

Referring to Wang et al. (2021b) and Lee and Lee (2022), this study selects the following indicators as the control variables: (1) total population (*Pop*; 10,000 people); (2) per capita GDP (*PGDP*; RMB), which is obtained by dividing the GDP by the total population; (3) energy intensity (*Eni*; standard coal/RMB 10,000), which is the ratio of total energy consumption to the GDP; (4) urbanization rate (*Urb*; %), which is the ratio of the urban population to the total population; (5) foreign direct investment (*FDI*; USD 100 million); and (6) government intervention (*Gov*), which is represented by the ratio of the fiscal expenditure to the GDP. The above indicators are from the *China City Statistical Yearbook* and statistical yearbooks of the various cities.

4. Empirical analysis

4.1. Descriptive statistics

The statistical description of each variable is shown in Table 1. Fig. 2 show the changing trends of CEE in each urban agglomeration, and the following findings can be obtained from Fig. 2. First, the average CEE of PRDUA is higher than that of the other urban agglomerations. This finding indicates that significant efficiency differences exist among the urban agglomerations. Second, the gap between the CEE of BTHUA and that of the other urban agglomerations has gradually widened. This finding illustrates that BTHUA pulls down the overall efficiency of the China's urban agglomerations. Third, the overall CEE of China's urban agglomerations remains inefficient, and a large gap in CEE exists between the cities. Therefore, the various urban agglomerations must focus on the green development of the inefficient cities.

4.2. Benchmark regression analysis

Preliminary steps are taken before conducting the regression analysis. First, the stationarity of the series is tested with the HT method, and the results show that the variables are stationary after the second-order

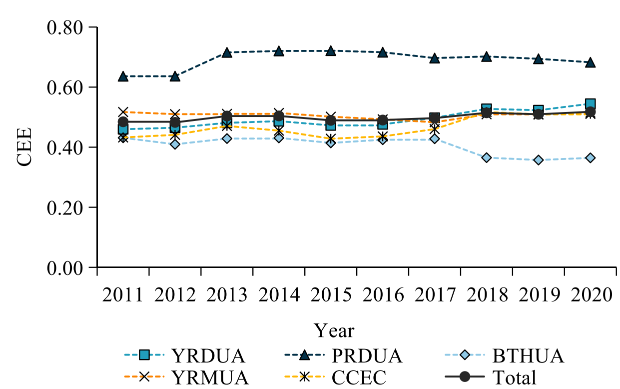

Fig. 2. CEE of urban agglomerations from 2011 to 2020.

Table 1
Descriptive statistics.

Type	Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Explained Variable	*CEE*	890	0.50	0.26	0.13	1.28
Core Explanatory Variables	*DF*	890	184.12	70.05	35.08	334.48
	DF_bre	890	174.65	68.54	20.19	326.49
	DF_dep	890	187.43	70.59	33.31	349.75
	DF_dig	890	209.39	85.84	12.49	340.01
Mediator Variables	*TI*	890	112.24	240.15	0.32	2326.58
	Ins	890	6.63	0.36	5.88	7.65
Control Variables	*Pop*	890	591.95	484.43	73.78	3208.93
	PGDP	890	64487.62	35495.76	15704.00	200171.00
	Eni	890	0.58	0.45	0.05	3.10
	Urb	890	56.56	16.16	18.19	100.00
	FDI	890	19.49	32.88	0.05	243.29
	Gov	890	0.18	0.07	0.06	0.66

difference processing. Second, the Kao and Perdroni test results reveal that the variables have a cointegration relationship. Finally, using a panel fixed-effects model through the Hausman test is reasonable.

Table 2 illustrates the outcomes of the benchmark regression model. Specifically, DF negatively affects CEE at the 1% significance level. This result suggests that the development of DF in the urban agglomerations does not promote the emissions reduction effect, which is in line with the conclusions of Zhao et al. (2021). The interpretation of this conclusion is as follows. First, this outcome is related to the total expansion effect of financial development on CO_2 emissions. The development of DF promotes the expansion of corporate production and increases energy demand and consumption, resulting in large CO_2 emissions, thereby increasing environmental pressure. Second, the development of DF also increases the CO_2 emissions of the upstream and downstream sectors of the digital sector. The development of DF is based on telecommunications, software and information technology services, and the Internet. The electricity consumption of such industries accounts for 6.9%–12% of the world's total electricity consumption (Lange et al., 2020). The supply of electricity in China is based mainly on thermal power generation. Therefore, the development of DF in China increases electricity demand, leading to high CO_2 emissions. Third, the main businesses of DF include digital payment, online small and micro-financing, and digital microinsurance. The green emissions reduction effect of such businesses cannot make up for the negative impact of DF on the environment during the development process.

Furthermore, the results remain robust after the introduction of the quadratic term of DF in the benchmark model. The regression results indicate that a U-shaped correlation exists between DF and CEE, which also confirms that the negative relationship between DF and CEE may be related to the fact that DF is in the infant stage of development, and its green effect has yet to appear. As DF matures, the green benefits it brings are huge and can make up for its pollution effects (Yu et al., 2022). Additionally, the results of M6 in Table 3 confirm the robustness of the U-shaped correlation between DF and CEE. The above results are also supported by Lee et al. (2022).

For the DF subdimension indicators, it can be seen that *DF_bre* and *DF_dep* significantly negatively affect CEE. Guaranteeing *DF_bre* and *DF_dep* requires many infrastructure facilities. Therefore, investment in numerous infrastructure projects will increase energy consumption and reduce CEE. In addition, credit business is the primary measure of *DF_dep*. The purchasing power of residents will increase significantly after obtaining consumer loans, and they will increase their consumption of large-ticket commodities, such as refrigerators, air conditioners, and cars (Khan and Ozturk, 2021). The production and use of such energy-intensive commodities increase fossil energy and electricity demand, raising CO_2 emissions. For SMEs, DF reduces the financing threshold and makes obtaining financing easy. According to enterprise life cycle theory, SMEs obtain financing mainly for scale expansion (Zhao et al., 2021). In addition, owing to the high-cost and long technology R&D cycle, SMEs lack the initiative to innovate low-carbon technologies. Therefore, for the sake of high profits, SMEs have little incentive to participate in environmental governance, thereby further increasing environmental pressure (Westman et al., 2021).

However, *DF_dig* has a significant positive correlation with CEE. Digitization strengthens the facilitation and mobilization of DF (Guo et al., 2020). Therefore, increasing digitization of DF can reduce resource waste, promote rational resource allocation, and improve CEE.

For the control variables, it can be seen that *Pop* and *PGDP* significantly affect CEE. The population scale effect increases productivity, thereby promoting CEE (Li et al., 2019). In addition, the increase in the per capita income level will prompt society to improve resource allocation efficiency and build a quality ecological environment. According to the environmental Kuznets curve, economic growth will eventually reduce environmental pollution and increase CEE (Kaika and Zervas, 2013). An increase in *Eni* can significantly reduce CEE mainly owing to China's energy structure, which is dominated by coal and oil consumption. Economic production activities consume abundant fossil energy and emit excessive CO_2, which in turn reduce CEE (Wang et al.,

Table 2
Regression results of benchmark model.

Variable	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*
ln *DF*	−0.5670*** (0.0523)	−1.4239*** (0.2909)			
$(\ln DF)^2$		0.1189*** (0.0397)			
ln *DF_bre*			−0.3064*** (0.0295)		
ln *DF_dep*				−0.2709*** (0.0558)	
ln *DF_dig*					0.0560*** (0.0207)
ln *Pop*	0.1373*** (0.0531)	0.1367*** (0.0529)	0.1240** (0.0538)	0.2378*** (0.055)	0.2466*** (0.0557)
ln *PGDP*	0.5868*** (0.0428)	0.5647*** (0.0432)	0.5781*** (0.0429)	0.5103*** (0.0446)	0.5070*** (0.0452)
ln *Eni*	−0.2323*** (0.0142)	−0.2368*** (0.0142)	−0.2374*** (0.0143)	−0.2333*** (0.0151)	−0.2337*** (0.0152)
ln *Urb*	−0.1068*** (0.0376)	−0.0972*** (0.0376)	−0.0986*** (0.0378)	−0.1117*** (0.0401)	−0.0970** (0.0404)
ln *FDI*	−0.0192*** (0.0073)	−0.0181** (0.0073)	−0.0169** (0.0074)	−0.0234*** (0.0077)	−0.0219*** (0.0078)
ln *Gov*	−0.1165*** (0.0277)	−0.1142*** (0.0275)	−0.1101*** (0.0279)	−0.1423*** (0.0291)	−0.1399*** (0.0296)
Constant	−5.4613*** (0.6948)	−3.7478*** (0.8975)	−6.3847*** (0.6766)	−6.4489*** (0.7576)	−7.8617*** (0.7011)
Individual Effect	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes
N	890	890	890	890	890
Cities	89	89	89	89	89
Within R^2	0.5280	0.5334	0.5229	0.4732	0.4624
F-statistic	54.89***	52.71***	53.77***	44.07***	42.20***
F-test	94.92***	93.38***	93.61***	83.56***	82.21***

Note: Standard errors are in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3
Stepwise regression results of mediating effect test.

Variable	M1	M2	M3	M4	M5	M6
	ln *CEE*	ln *TI*	ln *Ins*	ln *Ins*	ln *CEE*	ln *CEE*
ln *DF*	−0.5670***	0.7267***	0.0628***	0.0584***	−0.4835***	−1.2217***
	(0.0523)	(0.1686)	(0.0082)	(0.0082)	(0.0537)	(0.2893)
$(\ln DF)^2$						0.1020***
						(0.0393)
ln *TI*				0.0060***	−0.02657**	−0.0243**
				(0.0017)	(0.0110)	(0.011)
ln *Ins*					−1.0223***	−0.9964***
					(0.2257)	(0.2251)
Constant	−5.4613***	−16.1135***	1.5747***	1.6707***	−4.2796***	−2.8144***
	(0.6948)	(2.2400)	(0.1088)	(0.1116)	(0.7996)	(0.9762)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	890	890	890	890	890	890
Cities	89	89	89	89	89	89
Within R^2	0.5280	0.7218	0.7286	0.7327	0.5452	0.5491
F-statistic	54.89***	127.31***	131.70***	126.39***	52.15***	50.12***
F-test	94.92***	31.22***	16.01***	16.21***	98.00***	96.42***

Note: Standard errors are in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

2015). Urbanization is accompanied by industrialization and frequent economic activities, which increase energy demand and accelerate resource consumption (Wang et al., 2021a). Therefore, *Urb* significantly suppresses CEE. Moreover, *FDI* induces pollution transfer, which aligns with the pollution paradise hypothesis (Cheng et al., 2020). Therefore, a significant negative correlation can be seen between *FDI* and CEE. Finally, *Gov* significantly reduces CEE, which reveals that the government's fiscal expenditure structure is not rational, ignoring relevant investment in environmental protection in pursuit of economic growth, which can lead to the poor allocation of sustainable production factors, thereby hindering CEE improvement (Ma et al., 2021).

4.3. Analysis of mediating effect

This section analyzes the mediating effect of *TI* and *Ins* through the stepwise regression method, and the results are presented in Table 3. The regression results of M2 and M3 show that DF can significantly promote *TI* and *Ins*, which significantly affect CEE. The regression results of M1, M2, M3, and M5 indicate that *TI* and *Ins* have a mediating effect. To further verify whether the mediating effect of *TI* and *Ins* holds, this section tests the multiple mediating effects with the Bootstrap approach. The results in Table 4 reveal that the mediating effect of *TI* does not hold, but the mediating effect of *Ins* holds. The stepwise regression results indicate that *DF* can affect *Ins* by affecting *TI*, thereby affecting CEE. This section also verifies the chain mediating effect of *TI* and *Ins* with a Bootstrap test. The results in Table 5 show that the mediating effect of *TI* is not significant, whereas the mediating effect of *Ins* is significant. Meanwhile, the chain mediating effect of *TI* and *Ins* passes the significance test.

The regression results of M5 reveal that *TI* and *Ins* significantly negatively affect CEE. The reasons for the significant inhibitory effect of *TI* on CEE are as follows. DF can alleviate the financing constraints of enterprises, especially energy-intensive enterprises. The enterprises may promote investment in production-oriented technology research and development after obtaining financing (Lin and Ma, 2022). The technological progress improves production levels and energy efficiency, reduces production costs, but indirectly expands fossil energy consumption, thereby increasing CO_2 emissions and reducing CEE. This outcome demonstrates that the positive effect of technological progress is offset by the rebound effect (Wang and Wei, 2020).

Table 4
Bootstrap test results of multiple mediating effects.

Path	Coefficient	95% Confidence Interval	
		Lower Limit	Upper Limit
Direct Effect	−0.4835	−0.6129	−0.3612
DF −> TI −> CEE	−0.0193	−0.0474	0.0087
DF −> Ins −> CEE	−0.0642	−0.1057	−0.0283
Total Effect	−0.5670	−0.6817	−0.4370

Table 5
Bootstrap test results of chain mediating effect.

Path	Coefficient	95% Confidence Interval	
		Lower Limit	Upper Limit
Direct Effect	−0.4835	−0.6129	−0.3612
DF −> TI −> CEE	−0.0193	−0.0474	0.0087
DF −> TI −> Ins	−0.0598	−0.1001	−0.0260
DF −> TI −> Ins −> CEE	−0.0044	−0.0098	−0.0011
Total Effect	−0.5670	−0.6817	−0.4370

Moreover, *Ins* suppresses CEE improvement, which is also supported by Sun and Huang (2020) and Zhang and Liu (2022). China's tertiary sector is not well-developed and includes industries with high consumption and high emissions. For example, the Chinese transportation industry is expanding at an accelerated rate, and its CO_2 emissions are one of the major sources of greenhouse gases in China (Bai et al., 2020). According to the research of Li and Yu (2019), China's transportation industry is one of the largest fossil energy consumers, and its carbon emissions account for about 14% of the country's total emissions. Therefore, such factors can further hinder CEE improvement.

4.4. Heterogeneity analysis

This section analyzes the heterogeneity of the influencing factors of CEE. Table 6 shows the regression results for each urban agglomeration. First, DF significantly impacts only the CEE of YRDUA, PRDUA, and YRMUA. Among them, the significance level of YRDUA is the strongest, which may be because DF first emerged in China's Yangtze River Delta region and radiated to the other urban clusters in the country (Zhang et al., 2020). In addition, a prominent U-shaped connection exists between DF and CEE in YRDUA, PRDUA, and YRMUA. Second, *TI* significantly affects the CEE of the three urban agglomerations along the east coast. However, *TI* has a significant positive correlation only with the CEE of PRDUA, which indicates that PRDUA may pay more attention to green technology innovation and development than the other agglomerations, thereby inducing the green benefits of technological

Table 6
Regional heterogeneity analysis.

Variable	YRDUA	PRDUA	BTHUA	YRMUA	CCEC
	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*
ln *DF*	−2.1438***	−2.2860*	−0.6781	−1.1336**	0.8911
	(0.6387)	(1.3352)	(1.1201)	(0.5426)	(0.854)
$(\ln DF)^2$	0.2333***	0.3131*	0.0648	0.1351*	−0.1148
	(0.0808)	(0.1638)	(0.1508)	(0.0717)	(0.1156)
ln *TI*	−0.0999***	0.1855**	−0.0820**	0.006	0.0272
	(0.0278)	(0.0812)	(0.0336)	(0.0131)	(0.0224)
ln *Ins*	−2.2561***	1.5483	−2.1427*	−0.0675	1.0039
	(0.7916)	(1.8916)	(1.2107)	(0.2147)	(0.7152)
Constant	2.3974	−2.5912	−3.3277	−4.9587***	−12.7293***
	(1.9953)	(5.4721)	(3.7616)	(1.8241)	(2.5928)
Control Variables	Yes	Yes	Yes	Yes	Yes
Individual Effect	Yes	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes	Yes
N	260	90	130	250	160
Cities	26	9	13	25	16
Within R^2	0.6907	0.7960	0.6734	0.6388	0.6872
F-statistic	25.27***	12.73***	10.64***	19.18***	14.45***
F-test	51.66***	14.18***	87.09***	223.17***	68.06***

Note: Standard errors are in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

innovation. However, the technological innovation of YRDUA and BTHUA may be highly focused on economic benefits. Third, *Ins* significantly negatively affects only the CEE of YRDUA and BTHUA, which may be due to the well-developed logistics and transportation industry of YRDUA (Wang et al., 2019) and heavy industry of BTHUA, as its leading industry (Wu et al., 2020). Overall, the effects of *DF*, *TI*, and *Ins* on CEE have obvious regional heterogeneity characteristics.

4.5. Robustness test

A series of robustness and endogeneity tests show that the results of this study are robust and reliable. Referring to the practices of Zhang and Liu (2022) and Wang and Guo (2022), five robustness tests are conducted. In Table 7, M7 is the regression result after Beijing, Tianjin, Shanghai, and Chongqing are excluded from the sample. M8 is the regression result after the *Ins* indicator is replaced by the ratio of the tertiary industry's added value to the secondary industry's added value. M9 is the result of the regression using the Tobit model after CEE is reestimated with the undesirable output SBM model.

M10 and M11 are the estimated results using the instrumental variable (IV) method to solve the endogeneity problem of the core variables. For the two IVs, (1) referring to Nunn and Qian (2014) and Zhao et al. (2020), this study selects the product of the number of fixed-line telephones per 100 people in 1984 and number of Internet users nationwide in the previous year as the first IV. (2) Referring to Zhang et al. (2020), this study selects the product of the Hangzhou spherical distance and national DF average (excluding itself) as the second IV. M10 is the regression result of the fixed-effects (within) IV regression, and M11 is the estimation result of the 2SLS (IV-2SLS estimation). The underidentification and weak identification test results indicate that the selection of the IVs is appropriate.

From the regression results of each robustness test in Tables 7 and it can be seen that no significant difference from the previous regression results exists, which confirms that the empirical results of this study are

Table 7
Robustness test.

Variable	M7	M8	M9	M10	M11
	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*	ln *CEE*
ln *DF*	−1.1023***	−1.2318***	0.2313*	−0.1169***	−0.1169***
	(0.2927)	(0.2925)	(0.1265)	(0.0170)	(0.0169)
$(\ln DF)^2$	0.0943**	0.0984**	−0.0430***		
	(0.0397)	(0.0397)	(0.0141)		
ln *TI*	−0.0226**	−0.0287***	−0.0358***	−0.0580***	−0.0580***
	(0.0108)	(0.0110)	(0.0113)	(0.0123)	(0.0123)
ln *Ins*	−0.8521***	−0.0465***	−2.2127***	−1.8068***	−1.8068***
	(0.2225)	(0.0164)	(0.2554)	(0.2328)	(0.2312)
Constant	−3.6195***	−4.3705***	−3.8686***	−1.8008***	
	(0.9682)	(0.9178)	(0.8413)	(0.6101)	
Control Variables	Yes	Yes	Yes	Yes	Yes
Individual Effect	Yes	Yes	No	Yes	Yes
Time Effect	Yes	Yes	No	No	No
N	850	890	890	760	760
Cities	85	89	89	76	76
Within R^2	0.5549	0.5425		0.4842	0.4842
F-statistic	48.96***	48.80***			67.63***
Wald Chi^2			871.54***	64261.42***	
F-test	101.07***	93.95***		85.53***	
LR Test			1599.22***		
Underidentification Test					634.442***
Weak identification Test					4314.260 [19.93]
Sargan Statistic					6.675***

Note: Standard errors are in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

robust.

5. Conclusions and recommendations

This study examines the influencing factors of CEE in five national-level urban agglomerations in China and explores the impact mechanism of DF on CEE. First, a distinctive U-shaped correlation exists between DF and CEE. The coverage breadth and depth of use of DF significantly inhibit CEE, whereas the digitalization of DF can significantly promote CEE. Regarding the control variables, energy intensity, urbanization, foreign direct investment, and government intervention significantly reduce CEE, whereas population size and economic level significantly increase CEE.

Second, industrial structure upgrading has a mediating effect. In addition, technological innovation and industrial structure upgrading have chain mediating effects. However, technological innovation and industrial structure upgrading significantly inhibit CEE improvement. The conclusions show that the current technological innovation and industrial structure upgrading do not demonstrate emissions reduction effects.

Third, the impact of each explanatory variable on CEE exhibits heterogeneity. DF is significantly negatively correlated with only the CEE of YRDUA, and technological innovation is significantly negatively correlated with the CEE of YRDUA and BTHUA and significantly positively correlated with the CEE of PRDUA. Moreover, industrial structure upgrading significantly negatively impacts the CEE of YRDUA and BTHUA.

This study presents several policy implications based on the empirical results and analysis. First, DF has a U-shaped impact on CEE. Therefore, this study argues that China should promote new green infrastructure construction to carry digital technologies and digital platforms, such as 5G network base stations, big data centers, blockchain technology, and artificial intelligence services. In addition, strengthening the integrated development of DF and green finance can considerably promote financing support for green industries and green technology development projects. Furthermore, the coordinated development of DF and green finance can alleviate the negative effect of DF on CEE in the early stages of development.

Second, regarding the influence mechanism, industrial structure upgrading has a mediating effect, and technological innovation and industrial structure upgrading have a chain mediating effect. However, technological innovation and industrial structure upgrading do not exhibit the green emissions reduction effect, mainly because productive technological innovation and energy-intensive industries dominate China's economic development. Therefore, China should promote investment in digital, low-carbon, and energy-saving technology. Meanwhile, industrial restructuring within urban agglomerations must consider the rationality of the industrial layout and guide the low-carbon transformation of high-energy-consuming and high-emissions industries.

Third, the impact of the various influencing factors on CEE demonstrates significant heterogeneity. Local governments must promote DF development according to local conditions. For YRDUA, adjusting the existing financing project structure of DF and increasing support for green projects are necessary. Moreover, only the technological innovations in PRDUA show emissions reduction effects. Therefore, PRDUA should increase its green technology development and share its green technology achievements with the other urban agglomerations.

This study can be further extended in the future. For example, future research can further explore the moderating mechanisms of potential moderating variables of DF on CEE, such as government intervention and green finance. In addition, whether there is a spatial effect of DF on CEE is also worth exploring.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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