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Can digital economy improve urban ecological development? evidence based on double machine learning analysis

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The role of digital economy (DE) in improving urban ecological development (UED) has attracted scholarly attention. Additionally, traditional causal inference models encounter several challenges, such as model misspecification and the "curse of dimensionality." In response to these problems, the double machine learning method is applied to assess the effect of DE on UED. Leveraging data from 282 Chinese cities in 2006–2021, several valuable conclusions emerge. First, DE improves UED and positively contributes to ecological resilience and recovery. Second, promoting green innovation, enhancing environmental efficiency, and optimizing industrial structures are the pathways through which DE contributes to UED. Third, the influence of DE on UED displays heterogeneity. Based on the results, this work proposes relevant recommendations grounded in empirical research.

KEYWORDS

digital economy, urban ecological development, double machine learning, causal mediation model, causal inference model

1 Introduction

Urban areas are undergoing rapid development, which is accompanied by a swift influx of urban populations. As forecasted by UN-Habitat (2022), 68% of the global population will have been residing in urban regions by 2050. The rapid expansion of urbanization undoubtedly brings substantial risks to urban ecosystems, including environmental pollution, soil erosion, biodiversity loss, and geological disasters (Song et al., 2020). In this context, China must advance its urban ecological development (UED) to counteract the detrimental consequences of urbanization (Korhonen and Seager, 2008; Dong et al., 2022). China has increasingly prioritized UED in recent years. Notably, the restoration and protection of urban ecosystems have been included in China's 14th Five-Year Plan. However, urban ecosystems are confronted with numerous environmental pollution and ecological degradation issues (Zhang H. et al., 2023). Identifying new pathways for enhancing UED and fostering high-quality urban ecosystems is crucial.

Existing studies indicate a strong connection between digital economy (DE) and UED (Liu et al., 2024). However, several gaps remain in the existing research. First, the debate over the relationship between DE and UED is far from settled. On the one hand, DE has driven advancements in digital technologies (Farley and Voinov, 2016), thereby enhancing urban ecosystems' capacity for risk prediction and management. On the other hand, digital technologies require substantial energy support, which may lead to a surge in energy consumption, thus posing new threats to urban ecosystems (Hills et al., 2018; Chatti and Majeed, 2022). Second, the use of the difference-in-differences model in existing research for estimating policy effects is prevalent. However, traditional causal inference models encounter several issues, such as model misspecification and the curse of dimensionality, thus leading to reduced accuracy and credibility in estimating policy effects (Ling et al., 2024). Third, studies analyzing the impact mechanisms of DE on UED are limited.

This study tackles the aforementioned issues by evaluating the effect of DE on UED using the double machine learning (DML) method. Furthermore, this research explores the roles played by green innovation, environmental efficiency, and industrial upgrade in enhancing UED through DE. Finally, the heterogeneity of the effect of DE on UED is examined by considering urban geographical location and resource endowment.

The main innovations of this study are outlined below. First, the relationship between DE and UED has been debated. This study focuses on urban areas in China and confirms that DE promotes UED, thus providing new evidence. Second, differing from the approach taken by Wu et al. (2024), the DML method is employed to estimate how DE influences UED. This method adeptly mitigates concerns regarding model misspecification and the curse of dimensionality, thereby resulting in improved accuracy of estimation outcomes. Third, this work dissects the mechanisms by which DE influences UED from three angles: environmental efficiency, industrial upgrade, and green innovation, which further expands on the findings of Zhang W. et al. (2023). Fourth, whereas previous studies have concentrated on examining regional heterogeneity, this study broadens the scope to investigate how DE affects UED under different resource conditions (Zhang et al., 2021).

2 Literature review and theoretical hypotheses

2.1 Literature review

As an important catalyst, DE influences various fields, such as corporate sustainability and green growth (Shahbaz et al., 2022; Wang et al., 2023; Stamopoulos et al., 2024). At present, considerable scholarly interest in the relationship between DE and UED has emerged. The existing literature on this topic presents two opposing perspectives.

One view in the literature is that DE enhances UED. This perspective argues that DE promotes the development of digital technologies that improve UED. For example, Luo et al. (2022) argued that DE enhances green development, thereby improving urban ecological recovery. Hao et al. (2023) concluded that DE contributes to environmental management and resource allocation, thus improving economic ecological efficiency. Liu et al. (2024) validated that DE possesses green value and promotes UED. Chen and Yao (2024) demonstrated that DE boosts carbon emission efficiency, thereby strengthening the resilience of urban ecosystems. According to Li and Zhou (2024), DE aids in lowering carbon emissions, which improves the resistance of urban ecosystems.

In contrast to these optimistic views, other researchers highlight the potentially negative effects of DE on UED. DE, which is driven by information and communication technologies (ICT), results in substantial energy use and increased CO_2 emissions, thereby damaging urban ecosystems. For example, Lee and Brahmasrene (2014) investigated the connections among ICT, CO_2 emissions, and economic growth. They concluded that although ICT facilitates economic growth, it also contributes to a rise in CO_2 emissions. Additionally, Hills et al. (2018) took Fiji, South Pacific as a case and concluded that the adoption of innovative technologies has increased fossil fuel consumption. Asongu et al. (2018) used data from 44 countries from 2000 to 2012, which demonstrated that the rise in ICT utilization has contributed to high CO_2 emissions *per capita*. In addition, Avom et al. (2020) took 21 sub-Saharan African nations as an example and investigated the effect of ICT usage on CO_2 emissions. They found that ICT significantly increases CO_2 emissions, thus indicating that it has exacerbated environmental issues in the region. Chatti and Majeed (2022) analyzed panel data from 94 countries between 1998 and 2016 and found that ICT damages environmental quality.

The aforementioned studies indicate that the relationship between DE and UED continues to be contentious. Hence, the current study applies the DML method to assess the impact of DE on UED, thus offering new empirical evidence to inform this discussion.

2.2 Theoretical hypotheses

Promoting DE potentially bolsters UED (Herman and Oliver, 2023). First, DE contributes to enhancing ecological resistance. Digital technologies aid in establishing platforms for risk monitoring and early warning. These platforms enable cities to track unforeseen challenges swiftly and take proactive preventive actions, thereby boosting ecological resistance (Ghobakhloo, 2020). In parallel, DE can provide financial and technological support to facilitate the upgrading of urban ecological infrastructure, thereby enhancing the urban ecosystem's ability to cope with risks (Guo D. et al., 2023). Second, DE contributes to enhancing ecological recovery. DE has enabled the integration of data with traditional production inputs, thereby transforming the production mode that involves high investment, low efficiency, and high pollution (Carlsson, 2004). The resulting increase in the total factor productivity has accelerated the restoration of urban ecosystems. Additionally, the emergence of numerous industries, such as smart agriculture, intelligent manufacturing, and digital finance, have eradicated a multitude of high-energy-consuming and highly polluting industries (Ran et al., 2023). This development has not only strengthened economic vitality but also propelled the progression of green economic growth. Accordingly, Hypothesis 1 is proposed.

Hypothesis 1: DE significantly promotes UED.

DE propels innovation and application of digital technologies within urban settings, guiding UED (Filiou et al., 2023). First, DE represents a form of green economy. Digital technologies contribute to the innovation of green technologies (Dian et al., 2024). Green innovation not only aids cities in refining their ecological

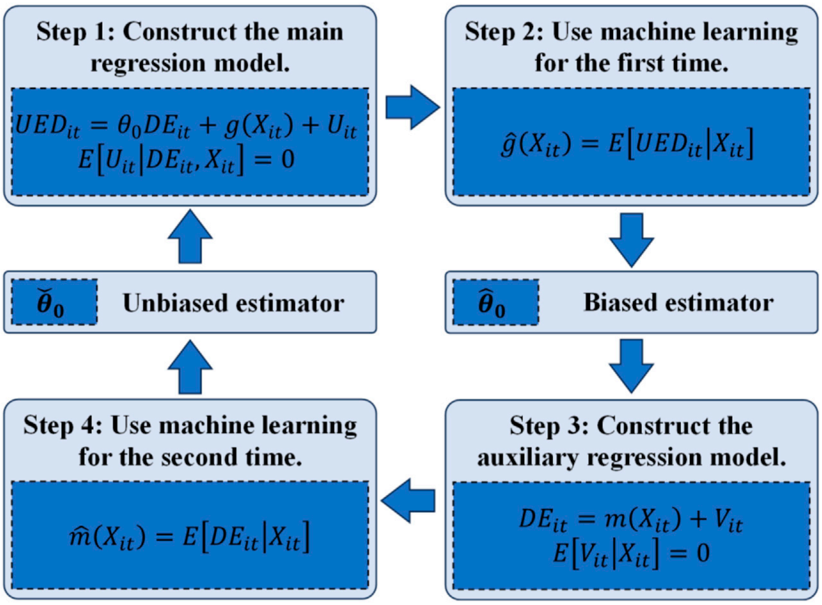

FIGURE 1
Steps for DML.

monitoring systems but also fosters the utilization of clean energy, thus contributing to decreased pollutant emissions. Second, DE has facilitated the integration of data elements with traditional production factors. This integration enables precise resource allocation and has reduced resource waste and pollution emissions (Lange et al., 2020), thereby enhancing environmental efficiency (Yasmeen et al., 2020). Improvements in environmental efficiency result in the conservation of resources and reduction of pollution (Hao et al., 2023). Third, DE optimizes the industrial structure by fostering innovation in emerging industries and accelerating the digitization of traditional sectors. Additionally, the shift of traditional industries from being labor intensive to becoming technology and knowledge intensive has transformed the energy consumption structure and resource utilization methods. As a result, urban energy consumption and environmental pollution have significantly decreased (Gu et al., 2023). Accordingly, Hypothesis 2 is proposed.

Hypothesis 2: DE reinforces UED by promoting green innovation, enhancing environmental efficiency, and optimizing the industrial structure.

The effect of DE on UED may differ depending on the characteristics of the city. In terms of geographic location, the eastern coastal areas demonstrate high economic prosperity and advanced infrastructure; thus, they offer a conducive environment for DE and result in a significant impact on UED (Xu and Cai, 2024). However, infrastructure development is comparatively deficient in the western inland areas; resources are scarce, which obstructs DE and diminishes their effectiveness in enhancing UED (Huang and Huang, 2024). In terms of resource endowment, DE can spur the emergence of industries in resource-based cities, thereby amplifying economic dynamism. However, the ongoing exploitation and utilization of resources aggravate the contradiction between ecological protection and economic development. Therefore, the positive impact of DE on UED in resource-based cities is low or even insignificant. Nonresource-based cities have strong resilience because of few shocks or disruptions caused by resource exploitation. Leveraging DE to transform traditional infrastructure concurrently enhances resource utilization efficiency in nonresource-based cities, thereby effectively boosting UED (Lyu et al., 2024). Therefore, Hypothesis 3 is proposed.

Hypothesis 3: UED exhibits heterogeneous effects on DE.

3 Methodology

3.1 Model

Numerous factors (e.g., policy, economy, society, and technology) affect the process of DE promoting UED. Moreover, the relationship between influencing factors is always nonlinear. Traditional models, such as differences-in-differences and propensity score matching, cannot apply to multidimensional data and have limitations in dealing with the nonlinear relationships between variables (Wen et al., 2024). This study addresses these problems by applying DML to explore how DE affects UED (Chernozhukov et al., 2018) (Figure 1).

Step 1: The main regression model is constructed, as presented in Equation 1.

$$\boldsymbol{UED_{it} = \theta_0 DE_{it} + g(X_{it}) + U_{it}, E[U_{it} \mid DE_{it}, X_{it}] = 0.} \quad (1)$$

In Equation 1, DE_{it} is an independent variable. If city i in year t implements DE, the value of DE_{it} is 1. Otherwise, it is 0. UED_{it} is a dependent variable, which represents UED in city i during year t θ_0 represents the treatment coefficient, X_{it} represents a group of control variables that influence UED_{it} through function g, and U_{it} is the error term.

Step 2: Machine learning algorithms are used for the first time.

The estimation $\hat{g}(X_{it})$ of function $g(X_{it})$ can be obtained using machine learning algorithms (Equation 2).

$$\hat{g}(X_{it}) = E[UED_{it} \mid X_{it}]. \tag{2}$$

The random forest (RF) algorithm is selected to estimate g because of the following reasons. First, compared with other algorithms, such as lasso and gradient boosting, RF is highly effective in handling high-dimensional data and has a strong ability to fit nonlinear relationships and feature interactions (Chernozhukov et al., 2018; Chen and Wang, 2024). Second, the superiority of RF in handling large datasets and complex relationships, particularly its high stability and accuracy during estimation, has been confirmed by previous research, (Wen et al., 2024).

Next, Equation 3 is further derived.

$$UED_{it} - \hat{g}(X_{it}) = \hat{\theta}_0 DE_{it} + \hat{U}_{it}. \tag{3}$$

Thus, the estimate of the disposal coefficient, $\hat{\theta}_0$, is given by Equation 4.

$$\hat{\theta}_0 = \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} DE_{it}\left(UED_{it} - \hat{g}(X_{it})\right). \tag{4}$$

In Equation 4, n represents the sample size. Although machine learning algorithms help reduce the variance of the estimator $\hat{\theta}_0$, they also cause regularization bias, which prevents $\hat{\theta}_0$ from converging to θ_0.

This study accurately examines the bias of estimator $\hat{\theta}_0$ by substituting Equation 1 into Equation 4, thus yielding Equation 5.

$$\begin{aligned}\hat{\theta}_0 &= \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} DE_{it}\left(\theta_0 DE_{it} + g(X_{it}) + \hat{U}_{it} - \hat{g}(X_{it})\right) \\ &= \theta_0 + \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} DE_{it}\hat{U}_{it} + \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} DE_{it} \\ &\quad \left(g(X_{it}) - \hat{g}(X_{it})\right).\end{aligned} \tag{5}$$

Next, Equation 5 is transformed into Equation 6.

$$\begin{aligned}\sqrt{n}\left(\hat{\theta}_0 - \theta_0\right) &= \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i=1}^{n} DE_{it}\hat{U}_{it} \\ &\quad + \left(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2}\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i=1}^{n} DE_{it}\left(g(X_{it}) - \hat{g}(X_{it})\right).\end{aligned} \tag{6}$$

In Equation 6, $(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2})^{-1}\frac{1}{\sqrt{n}}\sum_{i=1}^{n} DE_{it}\hat{U}_{it}$ is normally distributed with a mean of 0. However, in $(\frac{1}{n}\sum_{i=1}^{n} DE_{it}^{\,2})^{-1}\frac{1}{\sqrt{n}}\sum_{i=1}^{n} DE_{it}(g(X_{it}) - \hat{g}(X_{it}))$, the convergence rate of $g(X_{it})$ toward $\hat{g}(X_{it})$ is slow. As n approaches infinity, b also increases indefinitely. In addition, $\hat{\theta}_0$ has difficulty converging to θ_0.

Step 3: The auxiliary regression model is constructed, as presented in Equation 7.

This work addresses these issues by formulating the following auxiliary regression:

$$DE_{it} = m(X_{it}) + V_{it}, E[V_{it} \mid X_{it}] = 0. \tag{7}$$

In Equation 7, X_{it} affects the disposition variable via function m. V_{it} is the error term.

Step 4: The machine learning algorithm is used for the second time.

Similarly, the specific form of function $m(X_{it})$ is undisclosed. Its estimation $\hat{m}(X_{it})$ can be obtained using a machine learning model (Equation 8).

$$\hat{m}(X_{it}) = E[DE_{it} \mid X_{it}]. \tag{8}$$

The RF algorithm is applied to estimate function m.

Next, Equation 9 is further derived.

$$DE_{it} - \hat{m}(X_{it}) = \hat{V}_{it}. \tag{9}$$

Thus, the unbiased estimate of the disposal coefficient, $\breve{\theta}_0$, is derived, as shown in Equation 10.

$$\breve{\theta}_0 = \left(\frac{1}{n}\sum_{i=1}^{n} \hat{V}_{it} DE_{it}\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} \hat{V}_{it}\left(UED_{it} - \hat{g}(X_{it})\right). \tag{10}$$

Similarly, the estimation bias of estimator $\breve{\theta}_0$ is further examined, as presented in Equation 11.

$$\begin{aligned}\sqrt{n}\left(\breve{\theta}_0 - \theta_0\right) &= \left(E[V^2]\right)^{-1} \frac{1}{\sqrt{n}}\sum_{i=1}^{n} \hat{V}_{it}\hat{U}_{it} + \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\left(m(X_{it}) - \hat{m}(X_{it})\right) \\ &\quad \left(g(X_{it}) - \hat{g}(X_{it})\right) = a + b.\end{aligned} \tag{11}$$

In Equation 11, $\boldsymbol{a}$ normally distributed with a mean of 0 and the convergence rates of $m(X_{it})$ to $\hat{m}(X_{it})$ and $g(X_{it})$ to $\hat{g}(X_{it})$ determine the convergence rate of $\boldsymbol{b}$. This configuration results in a faster convergence rate for Equation 11 than for Equation 6. Therefore, $\breve{\theta}_0$ is an unbiased estimate of θ_0.

Based on the DML, a significantly positive $\breve{\theta}_0$ indicates that DE supports the development of UED, whereas a significantly negative $\breve{\theta}_0$ implies that DE impedes UED.

3.2 Variables

3.2.1 Dependent variable

This study selects UED as the dependent variable (Zhang T. et al., 2023). The UED evaluation indicator system constructed includes two dimensions: ecological resistance (Y1) and ecological recovery (Y2). Table 1 displays the specific indicators of the evaluation framework for UED. In contrast to subjective assessment methodologies, the entropy method mitigates the bias introduced by subjective judgments (Wang H. et al., 2024). Hence, the entropy weight method is utilized to assess UED. Specifically, the extreme value method is employed to ensure indicator comparability followed by normalization using Equation 12.

TABLE 1 UED evaluation indicator system.

Tier 1	Tier 2	Tier 3	Attribute
UED	Ecological resistance (Y1)	Volume of sulfur dioxide emission	-
		Volume of industrial particulate emission	-
		Population density	+
	Ecological recovery (Y2)	Ratio of wastewater centralized treated of sewage work	+
		Domestic garbage harmless treatment rate	+
		Proportion of green space in built district	+
		Per capita green space	+

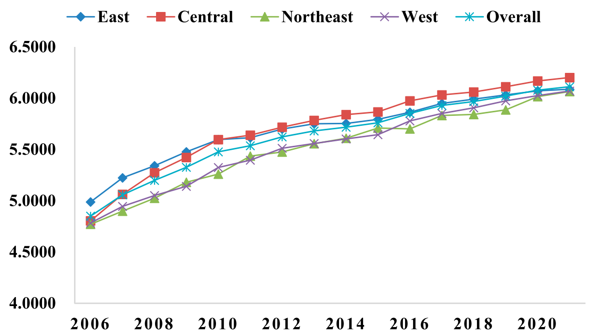

FIGURE 2
Overall and regional UED levels of China from 2006 to 2021.

Subsequently, the entropy e_j and coefficient of variation d_j for the indicators are computed with Equation 13 and Equation 14, respectively. Finally, the weights of each indicator w_j are obtained through Equation 15. The overall score of UED_{ij} is calculated in combination with Equation 16.

$$\bar{y}_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}}, \tag{12}$$

$$e_j = \left[-\frac{1}{\ln n}\sum_{i=1}^{n} \bar{y}_{ij} \ln \bar{y}_{ij}\right], \tag{13}$$

$$d_j = 1 - e_j, \tag{14}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, \tag{15}$$

$$UED_{ij} = \sum \left(y_{ij} \times w_j\right). \tag{16}$$

Figure 2 shows the overall and regional UED levels of China from 2006 to 2021. From an overall perspective, China's UED level experienced a significant upward trend throughout the observation period: this level rose from 4.8492 in 2006 to 6.1114 in 2021, which was a growth of 26.03%. This outcome suggests that China has made a remarkable achievement in the development of ecological civilization. Additionally, the UED levels in all four regions exhibited growth particularly in the central region, which recorded the highest growth rate at 29.11%. This growth may have resulted from the central region's shift from a traditional resource-dependent economy to a diversified, green, and sustainable economy (Fu et al., 2024), which has enhanced the ecological resilience and recovery of urban areas.

3.2.2 Independent variable

DE refers to an economic mode that is driven by digital technologies, thus leveraging data and digital technologies to facilitate industrial upgrade and economic growth (Luo et al., 2022). A binary variable is constructed based on the implementation of the National Big Data Comprehensive Pilot Zone (BDPZ) policy to represent DE. This study selects the BDPZ policy for three reasons. First, existing measurement approaches, such as internet penetration and e-commerce transaction volume, have notable limitations and cannot comprehensively capture the multidimensional nature of the DE (Chen and Yao, 2024). By contrast, pilot policies accurately reflect the actual effects of digital development because they integrate the deployment of digital technologies with policy innovation (Wei et al., 2023). Second, adopting pilot policies as a measure of DE, combined with DML, effectively addresses endogeneity and estimation biases that are caused by omitted variables (Lyu et al., 2024). Third, several studies have similarly employed a binary variable that has been constructed from the BDPZ policy to assess DE, including those by Liu et al. (2024) and An et al. (2024).

3.2.3 Mechanism variables

This study investigates how green innovation (M1), environmental efficiency (M2), and industrial structure (M3) mediate the effects of DE on UED (Hao et al., 2023; Xu and Cai, 2024).

Green innovation (M1). The quantity of green patent applications is used to quantify M1. It represents innovation activities that focus on conserving resources, improving energy efficiency, and fostering sustainable development (Lin and Ma, 2022). Given that M1 accurately reflects the output of green innovation, it serves as an effective indicator for evaluating green innovation (Dian et al., 2024). A high value of this metric suggests a high degree of advancement in green innovation.

Environmental efficiency (M2). By adhering to the definition of the World Business Council for Sustainable Development, this study posits environmental efficiency as the process through which cities gradually diminish pollution while concurrently fostering economic growth and enhancing the wellbeing of their residents (Luo et al., 2022). The global super efficiency slacks-based measure (SBM), which incorporates undesirable outputs, is employed to evaluate

TABLE 2 Input and output indicators.

Tier 1	Tier 2	Explanation
Input	Capital	Total fixed-asset investment
	Labor	Employees of unit at year-end
	Energy	Total energy consumption
	Land	Urban district area
	Water	Daily water consumption *per capita*
Desirable output	Economic output	Gross regional product
Undesirable output	Environmental pollution	Carbon dioxide emissions

environmental efficiency (Zhao X. et al., 2022). Building on prior research, this study selects several indicators, which are presented in Table 2.

Industrial upgrade (M3). The thriving of the tertiary sector marks a transition in economic growth from being predominantly driven by the secondary sector to being steered by the collaborative development of the secondary and tertiary sectors. Thus, the growth of the tertiary sector is utilized to evaluate industrial structural advancement (Zhao J. et al., 2022). M3 is assessed based on the share of the tertiary gross product in the gross regional product (GRP) (Cheng et al., 2018). An increase in M3 signifies a developed industrial structure.

3.2.4 Control variables

A range of control variables (X) are considered in this study for evaluation (Zhang H. et al., 2023; Lai et al., 2024): *per capita* GRP (X1), GRP growth rate (X2), secondary industry as percentage to GRP (X3), local expenditure as percentage to GRP (X4), loans and deposits of financial institutions as percentage to GRP (X5), number of industrial enterprises (X6), log value of urban district population (X7), total retail sales of consumer goods as percentage to GRP (X8), expenditure for education as percentage to local expenditure (X9), expenditure for science and technology as percentage to local expenditure (X10), number of students enrollment (X11), log value of highway passenger traffic (X12), log value of highway freight traffic (X13), road surface area *per capita* (X14), total import and export volume as a percentage of GDP (X15), and collections of public libraries (X16). Additionally, the quadratic term (X2) of all control variables is added to the model to enhance its accuracy.

3.3 Sample selection and data sources

In light of the policy implementation of the BDPZ, the sample is divided into a treatment group, which consists of 80 cities where pilot zones have been established, and a control group, which comprises all other cities. This study constructs a dataset with panel data from 282 prefecture-level cities in China in 2006–2021. The data for the indicators are primarily sourced from the China National Intellectual Property Administration and the City Statistical Yearbook. The descriptive statistics for all the variables are presented in Table 3.

TABLE 3 Descriptive statistics of variables.

Variable	N	Mean	SD	Min	Max
UED	4512	5.6359	0.5008	4.1500	6.4864
M1	4512	435.9353	1111.9777	1.0000	7474.0000
M2	4512	0.4958	0.1720	0.2600	1.0882
M3	4512	0.4072	0.1021	0.1881	0.7094
X1	4512	45759.7617	32298.4451	6276.0000	164000.0000
X2	4512	9.9217	4.3891	−2.9000	20.2000
X3	4512	46.7280	10.9719	18.1400	73.9200
X4	4512	0.1835	0.0939	0.0637	0.5815
X5	4512	2.3202	1.1026	0.8812	6.5029
X6	4512	6.5623	1.1050	3.9318	9.0561
X7	4512	4.1606	0.8790	2.5726	7.0480
X8	4512	0.3672	0.1028	0.1283	0.6643
X9	4512	0.1797	0.0408	0.0887	0.2847
X10	4512	0.0150	0.0143	0.0012	0.0775
X11	4512	3.8977	0.7620	1.7585	5.4121
X12	4512	8.3219	1.0684	5.3891	11.1513
X13	4512	8.9432	0.8584	6.7569	10.9023
X14	4512	16.3956	7.0667	4.2500	37.9800
X15	4512	13.7561	2.1110	8.6236	19.0780
X16	4512	5.3424	1.2706	2.9704	8.9709

4 Empirical analysis

4.1 Benchmark regression results

The results of the benchmark regression are shown in Table 4. Model 1 incorporates X and reveals that DE significantly promotes UED. Model 2 incorporates X and X2. The result of Model 2 maintains a significantly positive regression coefficient. This outcome implies that DE unlocks particular digital dividends, thus contributing to the enhancement of UED (Zhang W. et al., 2023). Therefore, H1 is supported. Models 3 to 6 examine the effects of DE from Y1 and Y2. The regression outcomes demonstrate that DE significantly enhances Y1 and Y2 at the 1% significance level, thus signifying its favorable impact on boosting resistance and recovery, which aligns with the theoretical insights of this research. DE can strengthen preventive measures against shocks or disturbances, thus alleviating their effects (Yang et al., 2023). Additionally, the digital dividends released by DE can facilitate urban ecological construction and foster green growth (Hao et al., 2023).

TABLE 4 Benchmark regression results.

Variables	UED	UED	Y1	Y1	Y2	Y2
DE	**0.0911*** **	**0.0955*** **	**0.0436*** **	**0.0439*** **	**0.0523*** **	**0.0507*** **
	(0.0193)	**(0.0192)**	**(0.0128)**	**(0.0128)**	**(0.0110)**	**(0.0109)**
X	Yes	Yes	Yes	Yes	Yes	Yes
X2	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	RF	RF	RF	RF	RF	RF
k-folds	5	5	5	5	5	5
Sample size	4512	4512	4512	4512	4512	4512

Note: *, **, and *** show that the disposition coefficient is significant at the 10%, 5%, and 1% level, respectively. The sample applies to the following tables.

TABLE 5 Regression results of DE on the mediating variables.

Variables	M1	M1	M2	M2	M3	M3
DE	**0.0083** **	**0.0083** **	**0.0249** **	**0.0276*** **	**0.0055** **	**0.0051** **
	(0.0037)	**(0.0036)**	**(0.0098)**	**(0.0099)**	**(0.0024)**	**(0.0024)**
X	Yes	Yes	Yes	Yes	Yes	Yes
X2	No	Yes	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	RF	RF	RF	RF	RF	RF
k-folds	5	5	5	5	5	5
Sample size	4512	4512	4512	4512	4512	4512

TABLE 6 Mechanism analysis.

Variables	Total	dir.treat	dir.control	indir.treat	indir.control
M1	**0.1239*** **	**0.1217*** **	**0.1037*** **	**0.0202*** **	**0.0022**
	(0.0164)	**(0.0165)**	**(0.0170)**	**(0.0054)**	**(0.0014)**
M2	**0.1286*** **	**0.1280*** **	**0.1143*** **	**0.0143*** **	**0.0006**
	(0.0164)	**(0.0164)**	**(0.0169)**	**(0.0050)**	**(0.0006)**
M3	**0.1228*** **	**0.1175*** **	**0.1039*** **	**0.0189*** **	**0.0054*** **
	(0.0164)	**(0.0166)**	**(0.0164)**	**(0.0060)**	**(0.0016)**

4.2 Mechanism analysis

Using the DML model, this section explores the effect of DE on the mediator variables (Table 5). The results show a statistically significant and positive regression coefficient. This finding suggests that DE contributes to promoting urban green innovation, enhancing environmental efficiency, and optimizing industrial structure (Gruber, 2019).

Furthermore, the causal mediation model is applied to analyze the mechanism of M1, M2, and M3 (Farbmacher et al., 2022). In this model, the indirect effect denotes the consequence of variations in mediator variable M while keeping the treatment variable DE fixed. The direct effect denotes the consequence of variations in treatment variable DE while keeping mediator variable M fixed. The treatment group is composed of 80 cities that have been adopting the BDPZ policy. Meanwhile, the control group contains the remaining cities. Table 6 presents the findings of the mechanism analysis. The total effects under diverse mediation routes are significantly positive. In the treatment group cities, the direct and indirect effects of all mediators are statistically significant. Cities that are strengthening

TABLE 7 DML Robustness analysis and endogenous analysis.

Variables	1	2	3	4	5	6	7
	UED	UED	UED	UED	UED	UED	UED
DE	**0.0879*****	**0.0951*****	**0.0932*****	**0.3701*****	**0.2964*****	**0.4538****	**0.8112****
	(0.0176)	**(0.0198)**	**(0.0150)**	**(0.0088)**	**(0.0179)**	**(0.2283)**	**(0.3522)**
X	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	RF	RF	Gradboost	Lasso	RF	RF	RF
k-folds	**3**	**8**	5	5	5	5	5
Sample size	4512	4512	4512	4512	4512	4512	4512

DE utilize their remarkable advantages in technology and economic development to propel green innovation (Yan et al., 2023), improve urban environmental efficiency, and optimize economic industrial structure (Ghobakhloo and Fathi, 2021), thus consequently driving UED growth. This outcome supports H2. In the control group cities, the direct effects of M1, M2, and M3 are significantly positive. Moreover, the indirect effects of M1, M2, and M3 are all positive. However, only the indirect effect of M3 is statistically significant. The findings indicate that even in cities that are not strengthening DE, urban areas consistently endeavor to optimize their industrial structure (Cheng et al., 2018), thus fostering favorable environments and conditions for enhancing UED.

4.3 Robustness tests

4.3.1 DML robustness analysis

While the DML method offers valuable insights for causal inference, it also has inherent limitations. For instance, the sample split ratio in K-fold cross-validation and the choice of machine learning algorithms can influence the results. Therefore, this section performs DML robustness analysis using the following approach: (1) altering the sample splitting ratio (Models 1 to 2 in Table 7), (2) changing the machine learning algorithms (Models 3 to 4 in Table 7), and (3) adopting an interactive model (Models 5 in Table 7). The regression outcomes still reveal that DE significantly and positively influences UED.

4.3.2 Endogenous analysis

The nonrandom selection of BDPZ gives rise to a potential endogeneity concern. This section employs a partial linear instrumental variable model to mitigate the endogeneity problem (Chernozhukov et al., 2018).

$$UED_{it} = \theta_0 DE_{it} + g(X_{it}) + U_{it}. \tag{17}$$

$$IV_{it} = m(X_{it}) + V_{it}. \tag{18}$$

In Equation 17 and Equation 18, IV_{it} refers to the instrumental variable for DE. This study constructs two instrumental variables (Guo B. et al., 2023). The first is the interaction term between the historical number of broadband internet access ports and the total volume of postal and telecommunications services in 1984 (IV1), and the second is the interaction term between the historical number of broadband internet access ports and terrain undulation (IV2). As shown in Model 6 and Model 7 of Table 7, DE promotes UED, thus verifying the robustness of findings.

4.3.3 Other robustness analysis

The following approaches are utilized to assess the robustness of baseline regression: (1) excluding special city samples (Model 1 in Table 8), (2) adjusting the time sample (Model 2 in Table 8), (3) considering the interaction effects of provinces and time (Model 3 in Table 8), and (4) excluding the influence of other parallel policies, such as SCP and BCP (Models 4 to 6 in Table 8). After retesting the effect of DE on UED using the aforementioned methods, the regression coefficients remain significantly positive.

4.4 Heterogeneity analysis

According to the geographical locations of the cities, the sample is categorized into four regions, as depicted in Table 9. Accordingly, the influence of DE on UED remains positive across different significance levels. This outcome indicates that despite variations in geographical locations and economic development levels among cities, DE consistently enhances UED effectively. The northeast region exhibits a low significance level in the relationship between DE and UED. This trend implies that the northeastern region must focus on the extensive development of DE to strengthen UED.

According to resource endowment, the sample cities are categorized into resource-based and nonresource-based cities. The results reveal that DE in nonresource-based cities significantly enhances UED (Table 10). Additionally, resource-based cities are further subdivided into growth, maturity, decline, and regeneration types. As shown in Table 10, although the regression coefficients of DE for the four types are positive, none of them are statistically significant. This outcome implies that

TABLE 8 Other robustness analysis.

Variables	1	2	3	4	5	6
	UED	UED	UED	UED	UED	UED
DE	**0.1012*****	**0.0885*****	**0.1215*****	**0.0939*****	**0.0922*****	**0.0940*****
	(0.0194)	**(0.0191)**	**(0.0296)**	**(0.0194)**	**(0.0193)**	**(0.0195)**
SCP				Yes		Yes
BCP					Yes	Yes
X	Yes	Yes	Yes	Yes	Yes	Yes
X2	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Learning model	RF	RF	RF	RF	RF	RF
k-folds	5	5	5	5	5	5
Sample size	4448	3948	4512	4512	4512	4512

TABLE 9 Regional heterogeneity analysis.

Variables	East	Central	Northeast	West
	1	2	3	4
	UED	UED	UED	UED
DE	**0.1222*****	**0.1278*****	**0.0805***	**0.2520*****
	(0.0342)	**(0.0440)**	**(0.0481)**	**(0.0469)**
X	Yes	Yes	Yes	Yes
X2	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Learning model	RF	RF	RF	RF
k-folds	5	5	5	5
Sample size	1376	1280	528	1328

resource-based cities must prioritize DE, which can help optimize their industrial structure, reduce reliance on traditional resource industries, and strengthen UED. The aforementioned conclusions confirm H3.

5 Discussion

5.1 Discussion of findings

First, DE contributes to advancing UED. This conclusion is in agreement with Wang T. et al. (2024), who proposed that DE reduces energy use and pollution via intelligent systems, thus contributing to ecological sustainability. Numerous scholars have demonstrated that the digital dividends unleashed by DE can effectively enhance the construction of smart urban ecosystems and improve ecological resilience (Liu et al., 2024). Moreover, DE, which is characterized by low pollution and low energy consumption, has fostered green urban growth and enhanced ecological recovery (Ma et al., 2024). However, some researchers hold differing opinions by arguing that DE can obstruct UED (Avom et al., 2020). This outcome may be a result of potential barriers in implementing digital strategies, such as insufficient funding, infrastructure disparities, and policy differences (Chatti and Majeed, 2022). The effect of DE is constrained by these barriers. Therefore, this study must address these challenges strategically to maximize DE's role in enhancing UED.

Second, this study finds that DE can promote UED by improving environmental efficiency, driving green innovation, and upgrading industrial structures. DE promotes the application of digital technologies in green innovation, which enhances green innovation output and alleviates environmental burdens. Qiu et al. (2025) concluded that DE promotes green innovation, thus further confirming this conclusion. DE has the potential to optimize production processes and enhance energy management efficiency, as confirmed by Luo et al. (2022) and Wu et al. (2024). Furthermore, DE advances the green and digital transformation of traditional industries, which facilitates industrial structural upgrading and drives UED. Ding and Luo (2024) asserted that DE accelerates the low-carbon and modern transformation of industries through technological and business model innovations, thus aligning with the findings of this study.

Third, this work demonstrates that UED exhibits heterogeneous effects on DE. In terms of geographical location, the northeast region exhibits relatively low significance in the positive effect of DE on UED. This outcome might be a result of enduring ecological issues, such as pollution emissions, which stem from the region's historical role as an old industrial stronghold, thereby counteracting some of the positive effects of DE (Xu and Cai, 2024). In terms of resource endowment, the beneficial effect of DE on UED is statistically insignificant in resource-based cities. The underlying reasons are

TABLE 10 Resource heterogeneity analysis.

Variables	Growing	Mature	Declining	Regenerating	Nonre
	1	2	3	4	5
	UED	UED	UED	UED	UED
DE	**0.0421**	**0.0519**	**0.0956**	**0.1109**	**0.0913*****
	(0.1257)	**(0.0519)**	**(0.0772)**	**(0.0737)**	**(0.0197)**
X	Yes	Yes	Yes	Yes	Yes
X2	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Learning model	RF	RF	RF	RF	RF
k-folds	5	5	5	5	5
Sample size	224	1008	368	240	2672

outlined below. One is the heavy reliance on traditional resources, which restricts the effectiveness of DE in resource-based cities during their growth, maturity, and decline phases (Wang et al., 2022). Additionally, resource regeneration cities undergo considerable instability during their transformation phase, which causes difficulty for DE to drive UED effectively (Lyu et al., 2024).

5.2 Theoretical implications

First, although extensive examination has been conducted on the relationship between DE and UED, the debate on their connection remains inconclusive. Some studies contend that DE boosts urban ecosystem resilience by advancing digital technologies, thus enhancing risk prediction and management (Farley and Voinov, 2016). Conversely, other studies highlight the energy demands of DE as a potential emerging threat to urban ecosystems (Chatti and Majeed, 2022). This study focuses on urban areas in China to provide new empirical evidence that confirms the positive effect of DE on UED. Therefore, it offers strong theoretical support for the role of DE in promoting urban ecological sustainability.

Second, traditional causal inference models often suffer from several issues, such as model misspecification and the curse of dimensionality, which potentially lead to biased results (Wu et al., 2024; Chen and Wang, 2024). This study employs the DML method to explore the relationship between DE and UER. This approach not only extends the application of DML but also effectively addresses the issues in traditional methods, thus enhancing the accuracy and reliability of results.

Third, this study focuses on three key pathways, namely, green innovation, environmental efficiency, and industrial upgrading, to explore the mechanisms through which DE affects UED. This work examines the mechanisms from multiple perspectives, thus further extending the work of Zhang T. et al. (2023). Furthermore, this research examines the heterogeneous effects under different resource conditions particularly in resource-based cities. Thus, it contributes comprehensively to the theoretical framework.

5.3 Practical implications

Cities in China have effectively implemented environmental monitoring and risk prediction by fostering DE and intensifying the application of digital technologies. Therefore, these activities have promoted UED. This experience may offer a useful reference for other regions or countries that are working to enhance UED. Accordingly, the following practical implications are presented.

First, digital policies should be enacted to maximize the potential of DE fully. Relevant authorities should establish a unified digital management platform for ecological environments, thus enhancing the capacity for risk prediction and environmental monitoring to bolster urban ecosystem resilience. In addition, the government should foster green and low-carbon economic growth and enhance urban ecological recovery. Cities also need to adopt digital governance measures to identify ecological issues accurately, which can enhance UED.

Second, policies should focus on the mechanisms through which green innovation, environmental efficiency, and industrial structure contribute to UED. The Chinese government should play an active role in establishing green innovation platforms and boosting investment in green innovation activities, thereby empowering green innovation. Meanwhile, industries with high pollution and energy consumption should establish monitoring platforms and resource management systems throughout the entire production process to improve resource efficiency. Cities should foster emerging industries and support agriculture, manufacturing, and other sectors in adopting digital transformation initiatives to achieve environmental sustainability.

Third, barriers must be overcome in implementing digital strategies, and regional differences must be bridged. Potential obstacles, including insufficient funds, infrastructure gaps, and regional policy inconsistencies, should be carefully considered. Governments at the local level must customize digital strategies based on their regional conditions and effectively coordinate resources, such as financial support and skilled labor. Emphasis should be placed on the northeast region and resource-based cities at various stages. Moreover, local governments should actively foster emerging industries in the northeast region. During the growth, maturity, and decline phases, resource-based cities should adjust their industrial frameworks. During the regeneration phase, the focus should shift toward improving environmental efficiency.

6 Conclusions and policy implications

This study uses data from 282 Chinese cities in 2006–2021 and utilizes the DML model to explore the effect of DE on UED, thus leading to the following conclusions. First, DE significantly enhances UED. DE contributes to the improvement of ecological resistance and ecological recovery of the urban ecological system. Second, DE enhances UED by fostering green innovation, enhancing environmental efficiency, and optimizing industrial structure. Third, UED exhibits heterogeneous effects on DE. In terms of geographic distribution, DE has a positive impact on UED across all four regions with different levels of significance. In terms of resource endowments, DE in nonresource-based cities promotes UED. However, the effect of DE on UED in resource-based cities is not statistically significant during the growth, maturity, decline, and rejuvenation stages.

This study also has several limitations. First, this research is based on 282 cities in China, thus making the conclusions particularly relevant to the improvement of UED in China. Future research should consider expanding the sample to include international cities to obtain a global perspective. Second, although this research considers mediating effects, moderating effects have not been explored. Future research can explore moderating factors, including policy interventions or social conditions, to understand how DE impacts UED.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YJ: Conceptualization, Methodology, Writing – original draft, Writing – review and editing. LL: Conceptualization, Supervision, Writing – review and editing. YX: Conceptualization, Supervision, Writing – review and editing.

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