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Assessing the impact of digitalization on environmental efficiency: Do population factors and institutional factors Matter?

Xiaoli Hao [a, c], Yuhong Li [b], Shufang Wen [a, c], Lulu Zhang [d, *]

[a] *Center for Innovation Management Research, Xinjiang University, Urumqi 830047, China*
[b] *School of Economics and Finance, Xi'an Jiaotong University, Xi'an 710049, China*
[c] *School of Economics and Management, Xinjiang University, Urumqi 830047, China*
[d] *College of Sciences, Shihezi University, Shihezi 832003, China*

ABSTRACT

The digital transformation provides an opportunity for the development of a green and low-carbon economy. This study used panel data collected from 30 Chinese provinces between 2011 and 2018, and assessed the impact of digitization (Dig) on environmental efficiency (EE). Quantile regression is employed to scrutinize the evolution of the marginal effect. From the perspectives of population and institutional factors, this study empirically investigates nonlinear relationships and potential mechanisms using Hansen threshold and mediation models. The findings reveal several key insights. Overall, levels of digitization and environmental efficiency (EE) are increasing with regional dispersion expansion, indicating a "polarization" characteristic. The impact of digitization on EE exhibits noticeable stage and regional heterogeneity. Analysis of population factors reveals that population structure, population size, and human capital trigger a sharp "marginal increase" of positive effects with single thresholds of 0.8155, 7.2284, and 11.0497, respectively. Analysis of institutional factors highlights the significance of fiscal policy quality (tax proportion), education expenditure, and tax system structure as important intermediaries. Finally, this paper presents corresponding policy implications.

KEYWORDS

Digitalization; environmental efficiency; population factor; institutional factor

* Corresponding author: Lulu Zhang
E-mail address: Xiatian112425@163.com
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1. Introduction

In emerging economies, the juxtaposition of rapid economic growth and environmental conservation has intensified in recent years (Li, 2003; Nchofoung and Asongu, 2022). Environmental efficiency epitomizes a fusion of economic quality and resource utilization. While economic expansion is pursued, the emphasis should be on enhancing energy utilization efficiency and environmental protection efficacy (Song et al., 2021; Wang et al., 2022; Xue et al., 2022). China has advocated for green development, framing harmony between humanity and nature as a guiding principle and promoting a green, low-carbon cycle as a core tenet within its "Five New Development Concepts". Pursuing this objective necessitates a shift towards intensive development to enhance environmental efficiency, as resource and environmental constraints dictate (Färe et al., 1989).

Simultaneously, in the socio-economic-environmental framework, traditional industries heavily rely on resource exploitation and processing, resulting in energy-intensive consumption and emissions that clash with efforts towards progressive energy conservation and emission reduction (Bian & Yang, 2010). This presents a significant challenge, underscoring the urgent need to enhance energy and environmental efficiency. However, Pigou's externality theory (Pigou, 1920) highlights the limitations of market mechanisms in addressing externalities, particularly those pertaining to environmental degradation, necessitating a blend of government intervention and market regulation (Boserup, M. 1980; Dasgupta, P. 1982). Institutional frameworks play a crucial role in fostering sustainable, green development (Hunjra et al., 2020), as evidenced by China's accelerated transition towards green and low-carbon practices.

Green development is propelled by institutional and technological innovations (Huang & Ye, 2017). Innovation serves as the primary catalyst for development and serves as the cornerstone for constructing a digital China and a smart society. Technological spillover effects expedite the conversion of innovations into productivity (Schumpeter, 1934). The digital economy serves as a transformative force, breaking away from traditional energy-intensive and environmentally harmful economic models, facilitating industrial upgrading, inclusive sustainable industrialization, the cultivation of green industries, and enhancing global value chain division of labor. However, the efficacy of innovation spillovers hinges on technology absorption capacity, which is influenced by population factors (Hao & Deng, 2019) and institutional dynamics (Bai et al., 2022). Addressing challenges related to population, institutions, and resources is imperative to maximize the role of digitalization in promoting environmental efficiency.

Hence, this study focuses on elucidating several key aspects: (1) The dynamic evolution of digitalization and environmental efficiency amidst China's rapid digitalization; (2) Understanding the influence trends of multidimensional population factors and maximizing the positive effects of digitalization on environmental efficiency; (3) Unraveling the specific mechanisms through which digitalization affects environmental efficiency within institutional frameworks; (4) Exploring the moderating role of resource endowment in regional heterogeneity. To achieve this, the study integrates digitalization, population factors, institutional dynamics, resource endowment, and environmental efficiency within a unified analytical framework, examining linear and nonlinear relationships, mechanisms, and regional disparities.

The remaining structure of this article is as follows: Section 2 presents the literature review; Section 3 conducts theoretical analysis; Section 4 outlines the research design; Section 5 presents empirical results and analysis; Section 6 conducts robustness tests; Section 7 further analyzes moderating effects; and finally, the concluding section synthesizes key findings and offers policy recommendations accordingly.

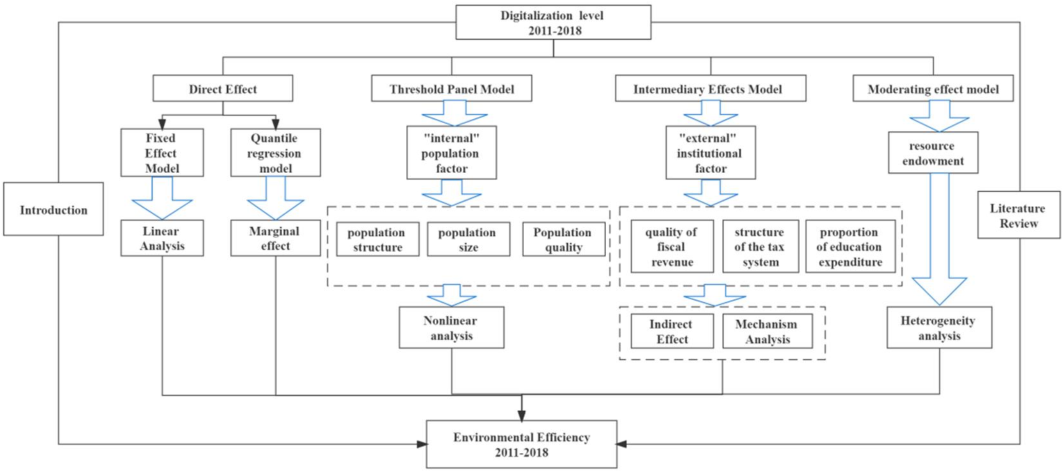

Figure 1. Research framework diagram.

2. Literature review

The environment, acting as a stringent constraint on the scale and pace of economic growth (Bi et al., 2014), and the digitalization strategy, hailed as a "new engine" for economic development (Xu & Zhang, 2020; Ren et al., 2021), have garnered considerable scholarly attention. Drawing from innovation theory (Schumpeter, 1934), Porter (1980) underscores innovation-driven development as a source of competitive advantage. The nexus between digitalization and environmental efficiency is underscored by Kuznets' inverted "U" curve, which elucidates economic growth as a conduit between the two (Grossman & Krueger, 1995; Shafik, 1994; Selden, 1995; Galeott et al., 2006). The Environmental Kuznets Curve (EKC) delineates a trajectory where environmental conditions initially deteriorate before gradually ameliorating during economic development, with variations across countries (Jayanthakumaran et al., 2012). Scholars debate the stability of the inverted U relationship between environmental quality and economic development (Arnaut & Lidman, 2021), influenced by critical factors such as income (Tachega et al., 2021), thus precluding generalizations regarding the economic-environmental relationship.

In examining the impact of digitalization, scholars primarily scrutinize its correlation with economic development. Extant research illustrates this linkage through avenues such as the circular economy (Bressanelli et al., 2018), market performance (Chen, 2020), and innovation performance (Teece, 2018). Shi et al. (2018) investigate how smart city construction policies influence urban environmental pollution, while Xu & Zhang (2020) introduce a novel measurement framework to gauge the enhancing effect of digitalization on economic development. With the economy's shift from rapid growth to high-quality development, scholars increasingly focus on digitalization and the environment (Tina et al., 2018; Ren et al., 2021; Xiang et al., 2022), revealing a close relationship between digitalization and environmental objectives (Tina et al., 2018). Ren et al. (2021) examine how internet development affects China's energy consumption and associated transmission mechanisms, while Xiang et al. (2022) investigate regional digitalization vis-à-vis low-carbon and green development, concluding an inverted U-shaped relationship.

Other influential factors center on population and institutional dynamics. Fundamentally, digitalization employs digital means to foster technological spillovers and recalibrate input-output relationships with new technological elements (Schumpeter, 1934). However, technological spillovers, as the driving force of innovation, hinge on technology absorption capacity, reflecting the quality of human capital (Kang & Lee, 2017). Additionally, institutional factors are pivotal; Pigou's externality theory (Pigou, 1920) illuminates how negative externalities stemming from market failures perpetuate inefficient resource allocation and environmental degradation. Concurrently, Schumpeter's innovation theory underscores how bounded rationality may be compromised by market failures due to positive technological externalities. The absence of compensation for this positive externality undermines market competition efficiency, necessitating policy intervention. Existing policy-focused research primarily examines the impact of environmental regulations and tax policies on environmental efficiency. Li & Zou (2018) ascertain that environmental regulations foster technological innovation and product upgrades to internalize environmental costs, while Ma et al. (2022) explore the relationship between natural resource taxes and the digital economy, highlighting the role of reduced taxes and increased investment in education to promote green innovation. However, digitalization presents challenges, including international taxation and tax regulations, taxation agency structures, and digital economy taxation (Tambunan & Rosdiana, 2020).

While existing literature confirms the impact of digitization on environmental efficiency in terms of economic growth, environmental regulation, and tax reduction policies, it remains unclear how to maximize its promotional effect across multiple dimensions. This paper endeavors to explore the maximization of digitalization's promotional effect on environmental efficiency from the vantage points of population and institutional factors. This study contributes in four main areas: Firstly, it delves into the marginal effects of digitalization development on environmental efficiency under different stages. Secondly, it examines the nonlinear relationship between digitalization and environmental efficiency concerning multidimensional population factors—urbanization rate, population size, and human capital quality. Thirdly, it investigates the influence channels of multidimensional institutional factors—fiscal revenue quality, tax structure, and educational investment. Lastly, apart from exploring linear and nonlinear relationships and mechanisms, this paper investigates regional heterogeneity.

3. Theoretical analysis

The impact of the digitalization on EE is essentially a manifestation of the spillover effect of science and technology, which is significantly constrained by the internal population factors and external institutional factors.

3.1. The direct effect of the digitalization on environmental efficiency

Kuznets posited that modern economic growth stems from an augmentation of resources, namely labor and capital input, or enhanced efficiency, or both. He contends that the direct contribution of labor and capital input is relatively minor, with the bulk of the remainder attributable to improvements in resource quality, alterations in resource allocation, and the impact of technological change. Technological spillovers resulting from digitalization play a pivotal role in economic growth. The crux of structural change lies in enhancing the efficiency of resource allocation. Blockchain technology has the potential to bolster the resource allocation capacity of the digital economy (Wu & Sun, 2021). Market-oriented economic development theory underscores that the market fosters competition, which in turn stimulates production efficiency. The blurring of market boundaries wrought by digitalization fortifies the market's dominant position, thereby positively impacting productivity. Positioned as a new engine of economic growth (Xu & Zhang, 2020), digitalization drives economic expansion and upgrades industrial structure (Pei et al., 2018).

3.2 The population factor effect

China's population structure undergoes a transition along the "quantity-quality" frontier, representing a shift from high fertility rates to an economy characterized by high human capital accumulation (Zhang et al., 2020). Using a threshold model, this study examines the nonlinear influence of multidimensional population factors: population structure, population size, and human capital quality.

(1) In terms of population structure, early urbanization stages prioritize speed over quality, resulting in significant resource and environmental costs. As urbanization progresses, there is increased focus on balancing environmental protection and economic development (Yan et al., 2019; Wu et al., 2019). With economies of scale and talent concentration, the positive externality of urbanization on environmental efficiency outweighs the negative impact of pollution emissions (Chen et al., 2020). Moreover, digitalization accelerates population movement, financial integration, and infrastructure development, potentially leading to nonlinear spillover effects on environmental efficiency resulting from urbanization.

(2) Considering population scale, population growth exacerbates resource consumption and environmental pollution, diminishing environmental efficiency (Ma et al., 2015). However, population growth also fosters economies of scale through technological progress, mitigating the adverse effects of population size (Morikawa, 2012). Higher population density, coupled with elevated living standards and education levels, enhances environmental consciousness and efficiency, positively impacting environmental quality, urban functionality, industrial structure, and spatial layout (Zeng, 2011). This could also result in nonlinear spillover effects of digitalization on environmental efficiency driven by population scale.

(3) From the perspective of human capital quality, higher education levels correlate with increased environmental awareness (Wu, 2017). Moreover, enhanced human capital quality boosts the absorption capacity for technological spillovers and fosters technological innovation, thereby improving environmental efficiency (Wang & Zatzick, 2019; Wu et al., 2021; Chen et al., 2022). Additionally, this may lead to nonlinear spillover effects of digitalization on environmental efficiency stemming from human capital quality.

3.3. The external institutions effect

This paper primarily examines external institutions, focusing on the structure of the tax system, the quality of fiscal revenue, and the proportion of education expenditure.

(1) Concerning the tax system's structure, digital technology innovation and cross-border data flow are reshaping the spatial layout and governance model of value chains, necessitating higher adaptive requirements for institutional policy design and environmental protection (Qi & Ren, 2022). Green development emphasizes institutional as well as technological innovation as fundamental driving forces (Sun et al., 2017; Li et al., 2021). A tax structure based on direct taxes can enhance tax collection efficiency (Abd Hakim, 2020). The Laffer curve illustrates that reasonable tax cuts can spur economic growth. Some scholars have found that natural resource taxes can significantly boost high-quality economic development (Ma et al., 2022). Therefore, the tax structure may be a crucial mechanism influencing environmental efficiency in the context of digitalization.

(2) Regarding the quality of fiscal revenue (the proportion of tax revenue), tax revenue significantly impacts economic growth by financing government investment expenditures (Gideon et al., 2020; Alpha, 2020). Digitalization elevates the government's digital governance level and information connectivity, expands the tax base, and improves management. High-quality fiscal revenue ensures environmental input guarantees, with potential benefits including promoting government-funded research (Forster & Stefan, 2014).

(3) Regarding the proportion of education expenditure, increased investment in education enhances citizens' education levels and ecological environmental awareness. This, in turn, promotes green consumption and energy conservation, stimulating enterprises to innovate green products from the demand side and thereby improving environmental efficiency.

3.4. Moderating effect of resource endowment

The characteristics of resource-based industries, characterized by high energy consumption and emissions, are at odds with the goals of progressive energy conservation and emission reduction (Wu et al., 2020; Xue, 2022). Traditionally, these industries have been centered around resource extraction and processing (Shao & Yang, 2014), leading to distorted allocation of labor factors and weakening the supportive role of the financial system in the real economy (Long et al., 2021). Additionally, mismatches in production factors, such as labor and capital, can distort market competition (Hoshi & Kim, 2013). However, in resource-based regions, digitalization holds significant potential to promote the development of smart energy systems and improve energy efficiency.

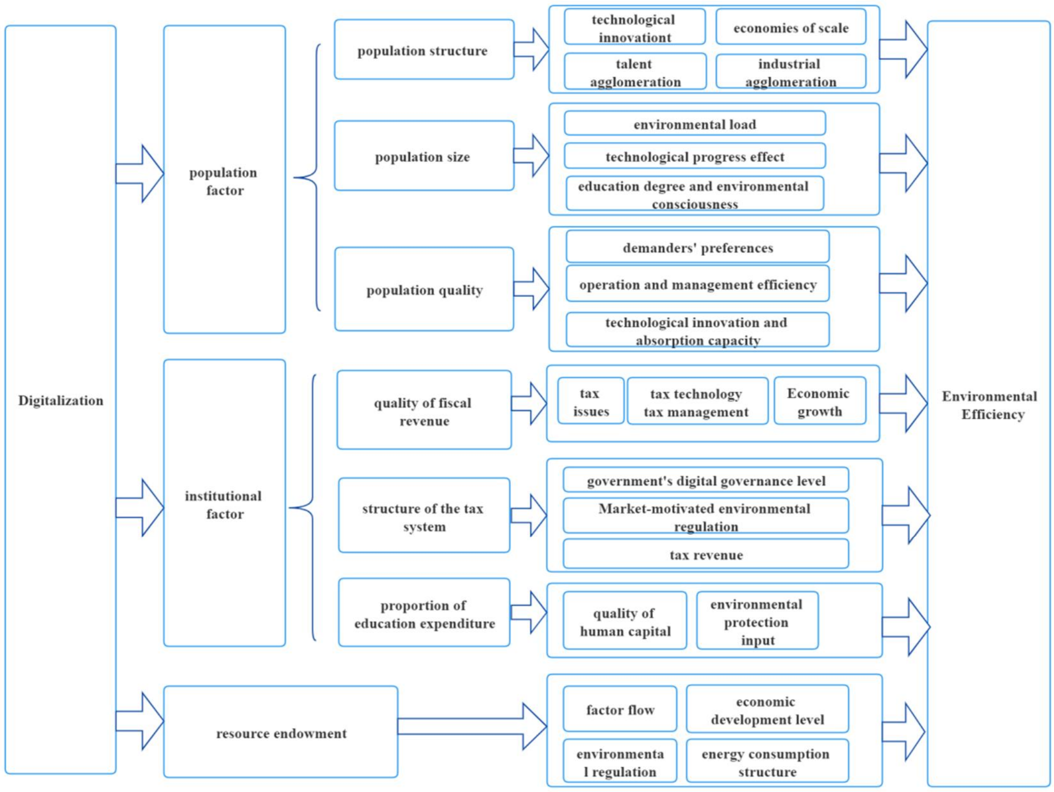

Figure 2. Mechanism Analysis Diagram.

4. Research Design

4.1 Model setting

To test the effect of digitalization on EE, the individual fixed effect model is constructed:

$$EE_{it} = \beta_0 + \beta_1 Digl_{it} + \beta cont_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

EE_{it} represents the environmental efficiency, i represent the province and t represent the year, $Digl_{it}$ is the digitalization level, $cont_{it}$ is the set of control variables, μ_i is the individual fixed effect of province i that does not vary over time, and ε_{it} is random disturbance.

According to Powell's (2022) non-additive fixed effects panel quantile model (QRPD), the panel quantile estimation is introduced into the instrumental variable method framework for parameter estimation, in the random disturbance term. The inclusion of fixed effects ensures the inseparability of random disturbance terms, the QRPD model estimates the coefficients more accurately, and the results are more robust (Ma et al., 2022). In this paper, the 10%, 30%, 50%, 70%, and 90% quantiles are selected to construct the QRPD model as follows:

$$Q_{EE_{i,t}} = \theta(\tau)Digl_{i,t} + \beta(\tau)cont_{i,t} \tag{2}$$

τ denotes the quantile, $Q_{EE_{i,t}}$ is the environmental efficiency at the corresponding quantile, $Digl_{i,t}$ is the level of digitalization development at the corresponding quantile, and $cont_{i,t}$ is the control variable. In the QRPD model, the regression coefficient at quantile τ indicates the effect of the explanatory variables on the explanatory variables at quantile τ (Ma et al., 2022). The adaptive Monte Carlo method (Adaptive-MCMC) was chosen to estimate the QRPD model.

Based on the theoretical analysis above, the nonlinear effects of the digitalization on environmental efficiency may be caused by multi-dimension population factors. Therefore, the panel threshold regression (Hansen,1999) is set:

$$EE_{it} = \phi_0 + \phi_1 Digl_{it} \times I(Urban \leq \theta) + \phi_2 Digl_{it} \times I(Urban > \theta) + \phi_c Z_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

$$EE_{it} = \phi_0 + \phi_1 Digl_{it} \times I(Lnpop \leq \theta) + \phi_2 Digl_{it} \times I(Lnpop > \theta) + \phi_c Z_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

$$EE_{it} = \phi_0 + \phi_1 Digl_{it} \times I\big(Q\hbar c \leq \theta\big) + \phi_2 Digl_{it} \times I\big(Q\hbar c > \theta\big) + \phi_c Z_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

The threshold variables $Urban_{it}$, Ln pop_{it}, and $Qhc_{it}$are urbanization rate, logarithm of total population, and quality of human capital, and $I(\cdot)$ is an indicator function that takes the value of 1 or 0.

According to the above analysis, in the process of high-quality economic development, the digitalization transforms the economic development mode, optimizes the allocation of factors, and at the same time highlights the problem of uncoordinated tax system structure. According to Jiang's (2022) mediation effect test method, this paper constructs a mediation effect model for external institutional mediation variables as follows:

$$EE_{it} = \beta_0 + \beta_1 Digl_{it} + \beta cont_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

$$R_{tax_{it}} = \alpha_0 + \alpha_1 Digl_{it} + \alpha cont_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

$$S_{tax_{it}} = \alpha_0 + \alpha_1 Digl_{it} + \alpha cont_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

$$Edu_{exp_{it}=\alpha_0} + \alpha_1 Digl_{it} + \alpha cont_{it} + \mu_i + \varepsilon_{it} \tag{9}$$

Each mediating variable measuring the external system, R_tax_{it} is the quality of fiscal revenue, S_tax_{it} is the structure of the tax system, and $Edu\_\exp_{it}$ is the share of education expenditure.

This paper draws on the ten resource-based provinces in the empirical research of Zhang et al. (2021), and constructs dummy variables for heterogeneity analysis based on whether they are resource-based provinces. Adding the multiplication term of the digitalization and “whether it is a resource-based province”, the adjustment effect model is constructed as follows:

$$EE_{it} = \beta_0 + \beta_1 Digl_{it} + \beta_2 D_i \times Digl_{it} + \beta cont_{it} + \mu_i + \varepsilon_{it} \tag{10}$$

$D_i$is a dummy variable for resource-based provinces, where is the resource-based province dummy variable, which takes the value of 1 if the province is a resource-based province and 0 otherwise. $D_i \times Digl_{it}$is the cross-multiplication term between the digitalization and the moderating variable.

4.2. Variables and data sources

4.2.1 Environmental efficiency (EE)

EE measures the ratio of environmental and economic input to output, and is calculated using the SBM-DEA model (Shen, 2012), in which inputs, expected outputs and undesired outputs are as follows.

Table 1. Input-output variables and sources.

EE process	Definition	Variable selection
Environment efficiency inputs	According to existing research, environment efficiency is a combined reflection of economic quality (directly related to labor and capital) and resource utility (directly related to energy).	Labor input, measured by Year-end total employment. Capital investment measured by capital stock. Energy input, measured by energy consumption.
Environment efficiency outputs	According to existing research, Environment efficiency outputs include desired outputs (economic outs) and undesired outputs (environmental pollution).	Desired outputs, measured by regional real GDP. Undesired outputs, measured by environmental pollution level

To capture the dynamic evolution process of the absolute difference change in core variables, we analyzed the distribution dynamic characteristics of environmental efficiency using kernel density estimation.

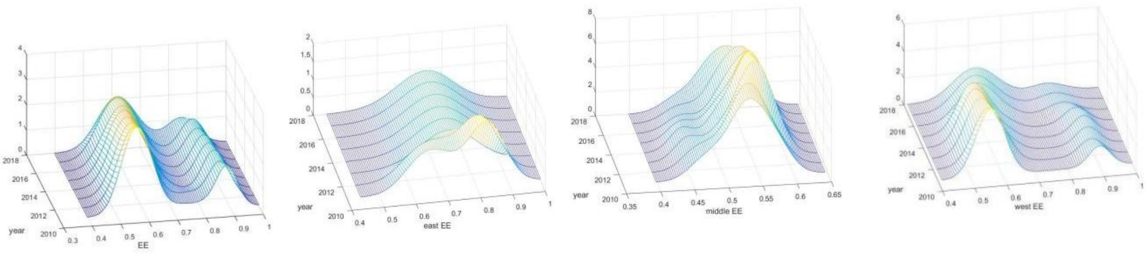

Figure 3. Dynamic evolution process of environmental efficiency across the country and the three major regions.

In the dynamic evolution process of environmental efficiency, the overall distribution curves for China and its three major regions — East, West, and Central — exhibited a slight upward trend over the study period, indicating a modest increase in environmental efficiency across the board.

Regarding distribution patterns, the overall curve displayed a trend of decreasing peak height and widening width, suggesting an overall expansion in the dispersion of environmental efficiency. Specifically, in both the Eastern and Western regions, the main peak of the distribution curve decreased in height while broadening in width, indicating a growing disparity in environmental efficiency within these regions. In the Central region, the main peak initially increased in height before decreasing, signaling an overall improvement in performance alongside an expanded width.

In terms of distribution extensibility, the overall curve demonstrated a widening trend, mirroring the trends observed in the Central and Western regions. The gap between provinces with higher environmental efficiency and the average level increased, although this trend was less pronounced in Eastern China.

Regarding polarization characteristics, the distribution curves for the entire country and Western areas exhibited a double-peak phenomenon, indicating polarization in environmental efficiency. The Central region displayed a weak trend of multipolar polarization, while the Eastern region underwent a “bipeak-unimodal” evolution process, with overall polarization characteristics weakening over time.

4.2.2. Digitalization (Dig)

Referring to the research of Bai & Zhang (2021) and Zhao et al. (2021), is measured by the index system (Table 2) from the four perspectives of digitalization foundation, digitalization popularization, digitalization scale and digitalization potential. The weight is determined through the extreme entropy method.

Table 2. Evaluation Index System of Digitalization level.

Target level	Criterion level	Index level
Digitalization level	Digitalization foundation	Fiber optic cable length/per square kilometer Number of broadband ports per capita Number of computer-reading rooms Number of cell phones per capita Broadband penetration rate (%) Network TV subscriber rate (%)
	Digitalization popularization	
	Digitalization scale	Total business volume of telecommunication industry (billion yuan) Added value of tertiary industry (billion yuan)
	Digitalization potential	R&D personnel in one region (10,000 people) Total number of R&D projects in one year R&D intensity (%) Number of employees in information technology industry (10,000 people)

4.2.3. Dynamic evolution

The distribution dynamic characteristics of digitalization level were analyzed by kernel density estimation. Results are shown in Fig. 4.

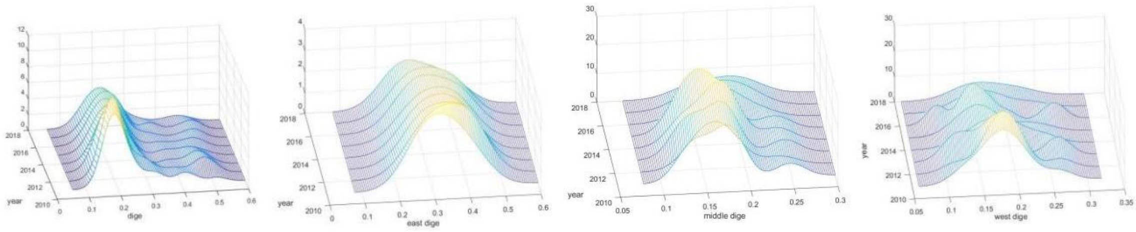

Figure 4. Dynamic evolution process of digitalization level across the country and the three major regions.

In terms of the dynamic evolution process, the overall distribution curve for the entire country, including the East, West, and the three major regions, exhibited a slight upward trend over time, indicating an improvement in the level of digitalization development across all regions.

Regarding distribution patterns, the overall distribution curve for China displayed a trend of decreasing peak height and increasing width of the main peak, signifying an overall expansion in the dispersion of digitalization development levels. There was no significant change in the height of the main peak of the distribution curve in the East, while the evolution in the Central and Western regions remained relatively consistent. The height of the main peak initially increased before decreasing, resulting in an overall decrease in performance and an expansion in width.

From the perspective of distribution extensibility, the distribution curves for the national, Central, and Western regions showed a noticeable right-trailing phenomenon, with some provinces demonstrating relatively high levels of digitalization development. The extensibility of the distribution curves for the entire nation and all three regions displayed a trend of broadening, albeit not distinctly, and convergence, respectively.

Considering polarization characteristics, the distribution curve for the entire nation, as well as the Western region, exhibited a bipolar or multipolar differentiation phenomenon. Over time, the Central region underwent an evolution process of “bimodal-unimodal”, leading to a weakening of overall polarization characteristics.

Threshold variables. From the perspective of population factors, include population structure (urbanization rate), population size, the quality of human capital (average years of education).

Intermediary variables. From the perspective of institution factors, include the tax structure, the quality of fiscal revenue (tax proportion), and the proportion of education expenditure.

Control variables. To obtain an objective estimate, include industrial structure, per capita GDP growth rate, finance budget and opening degree (FDI, import and export volume).

In addition, the energy consumption structure (*Ecs*), carbon emission (*Lncarb*) are used as the replacement variables for environmental efficiency to conduct robustness tests.

Table 3. Descriptive statistical.

Variables	Description	mean	sd	min	max
EE	the ratio of environmental and economic input to output	0.664	0.214	0.399	1
Dig	Composite Index of the Level of Digitalization	0.218	0.107	0.0600	0.600
Urban	The ratio of urban population to the year-end population	0.577	0.124	0.350	0.896
Lnpop	The logarithm of permanent population of the region at the end of the year	8.202	0.741	6.342	9.421
Qhc	The quality of human capital is an agent variable based on the average number of years of schooling of the total labor force population	10.15	0.773	8.394	12.96
S_tax	The ratio of direct tax to indirect tax. Indirect tax includes value-added tax, consumption tax, business tax, customs duty, resource tax, and urban maintenance and construction tax.	0.655	0.144	0.280	1.185
R_tax	The ratio of tax revenues to fiscal revenues	0.741	0.0792	0.570	0.960
Edu_exp	The ratio of local education expenditure to financial general budget expenditure	0.165	0.0260	0.0989	0.222
pGDP_g	The GDP per capita	0.0989	0.0492	-0.0211	0.245
Inds	The ratio of tertiary industry output to GDP	0.480	0.0893	0.327	0.831
Lnfdi	The logarithm of actual foreign capital utilization in regions	3.606	1.705	-3.219	5.879
Lntrade	The logarithm of total import and export volume	6.140	1.536	1.881	9.298
Lnfbr	The logarithm of local general finance budget revenue	7.552	0.828	5.023	9.401
Ecs	The ratio of coal consumption after conversion of standard coal to energy consumption	0.672	0.309	0.0271	1.731
Lncarb	The logarithm of CO2 emission	10.41	0.727	8.493	11.91

5. Empirical Results

5.1. Benchmark Regression

The linear regression results of the impact of the digitalization on environmental efficiency are shown in Table 4. Model (2) is mixed squares regression, and Column (3)-(4) are fixed effect models.

From the perspective of the core explanatory variables, in column (1) where only core variables are considered, the estimated coefficients of digitalization are significantly positive. Similarly, in model (3) incorporating control variables and provincial fixed effects, the coefficient of digitalization stands at 0.137. These results suggest that digitalization continues to exert a significant positive impact on environmental efficiency. This phenomenon may be attributed to the economic benefits generated by digitalization across various domains, including technological innovation, entrepreneurship, consumption, and social security.

The influence of total population on environmental efficiency is significantly negative, indicating that the pressure from population growth on resources and the environment outweighs the positive effects of technological progress resulting from scale economies. Import and export, on the other hand, have a significantly positive effect on environmental efficiency. This finding suggests that China's foreign trade contributes positively to environmental efficiency within the global value chain division of labor. Song Malin et al. (2012) also noted a significant positive impact of import volume on environmental efficiency.

Furthermore, the impact of economic development on environmental efficiency is significantly positive. Economic development facilitates environmental efficiency through industrial upgrading and a syphon effect, which fosters human capital agglomeration and the spillover of talent and technology.

Table 4. Benchmark regression results.

	(1) EE	(2) EE	(3) EE	(4) EE
Dig	0.134***	0.144***	0.137***	0.134***
	(5.820)	(2.98)	(3.096)	(3.075)
Lnfdi		0.006	0.003	0.002
		(1.600)	(0.870)	(0.469)
Lnpop		-0.160***	-0.171**	-0.230***
		(-5.52)	(-2.268)	(-2.969)
Lnfbr		0.014	0.012	0.018
		(1.060)	(0.961)	(1.321)
Lntrade				0.016**
				(2.537)
pGDP_g				0.064*
				(1.895)
_cons	0.635***	1.817***	1.936***	2.274***
	(122.298)	(8.19)	(3.273)	(3.812)
Province fixed	YES		YES	YES
N	240	240	240	240
R2	0.139	0.164	0.167	0.204

*Note: T-value in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*

5.2. Quantile Regression

Using Powell's (2015) non-additive fixed-effects panel quantile model (QRPD), we incorporate panel quantile estimation into the instrumental variable method framework to observe the marginal effect and dynamic evolution trajectory of digitalization development on environmental efficiency across various development stages more intuitively and accurately (Ma et al., 2022). In this study, we construct the QRPD model with quantiles of 10%, 30%, 50%, 70%, and 90%.

Table 5. Quantile regression results.

			EE		
	(1) 10	(2) 30	(3) 50	(4) 70	(5) 90
Dig	0.6765***	0.2507	1.3825***	0.4969	1.7056***
	(3.2383)	(0.7302)	(14.9191)	(1.3878)	(50.6863)
pGDP_g	0.0398	-0.3810**	0.6850***	0.5362	0.0732
	(0.2258)	(-1.9669)	(11.3904)	(1.3452)	(0.3248)

Inds	0.1937**	0.7862***	0.0690*	0.2273	-0.8862***
	(2.1452)	(6.5927)	(1.7140)	(0.9281)	(-5.5997)
Lnpop	-0.2304***	-0.2894***	-0.1754***	-0.4731***	-0.2024***
	(-12.8085)	(-6.7304)	(-13.4398)	(-4.8602)	(-12.9362)
Lnfdi	0.0568***	-0.0152	0.0214***	0.0482***	-0.0062
	(8.6486)	(-1.6054)	(4.2645)	(3.4371)	(-0.6884)
Lntrade	0.0257*	0.0453***	0.1019***	0.1984***	0.1710***
	(1.9533)	(3.4975)	(16.0682)	(6.1306)	(6.3956)
Lnfbr	-0.0467	0.1372*	-0.1993***	-0.0930	-0.2692***
	(-1.2650)	(1.7591)	(-12.2568)	(-1.3963)	(-5.8505)
Province fixed	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES
Obs	240	240	240	240	240

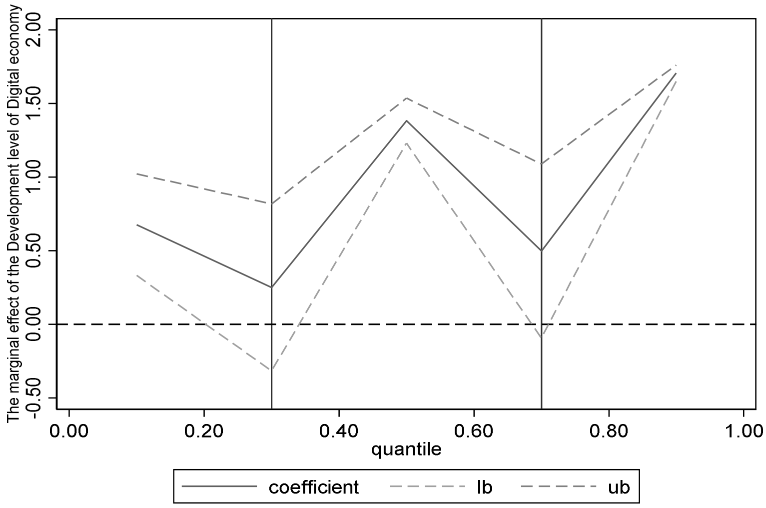

Figure 5. Marginal effect of digitalization development in quantile regression.

Table 5 reveals disparities in the regression coefficients of identical variables between the panel model and the QRPD model, as well as variations in the estimated coefficients of each variable across different quantiles, suggesting divergent influencing factors at various environmental efficiency stages. Notably, digitalization exhibits a significantly positive effect on environmental efficiency at the 90% quantile, underscoring its importance in enhancing regional environmental efficiency across different stages.

Figure 5 illustrates quantile positions ranging from 10% to 30%, 30% to 50%, 50% to 70%, and 70% to 90%, respectively. Across all quantiles, the marginal effects of digitalization are positive, with an evolving trajectory of downward-upward-downward-up. These findings highlight the dynamic changes in the marginal effect of digitalization development across different environmental efficiency stages. In the initial phase of environmental efficiency development, the impact of digitalization on environmental efficiency is modest and exhibits a downward trend. However, in subsequent stages, although the marginal effect of digitalization development fluctuates, it consistently exceeds that of the initial stage.

5.3. Threshold Results Analysis of Population factors

5.3.1 Existence test of threshold

Considering the EKC curve, this part explores the nonlinear heterogeneous effects of digitalization on environmental efficiency through the threshold model. Based on the panel threshold regression model (PTR) of Hansen (1999), this paper takes urbanization rate, natural logarithm of total population, and quality of human capital as the threshold variables, all significantly passing the single threshold. On this basis, further analysis was carried out to obtain the threshold value at the 95% significance level.

Table 6. Existence test of the threshold.

Threshold variables	Number of Thresholds	F value	P value	bootstrap
Urban	Single Threshold	52.00	0.0030	300
Lnpop	Single Threshold	59.47	0.0200	300
Qhc	Single Threshold	41.03	0.0067	300

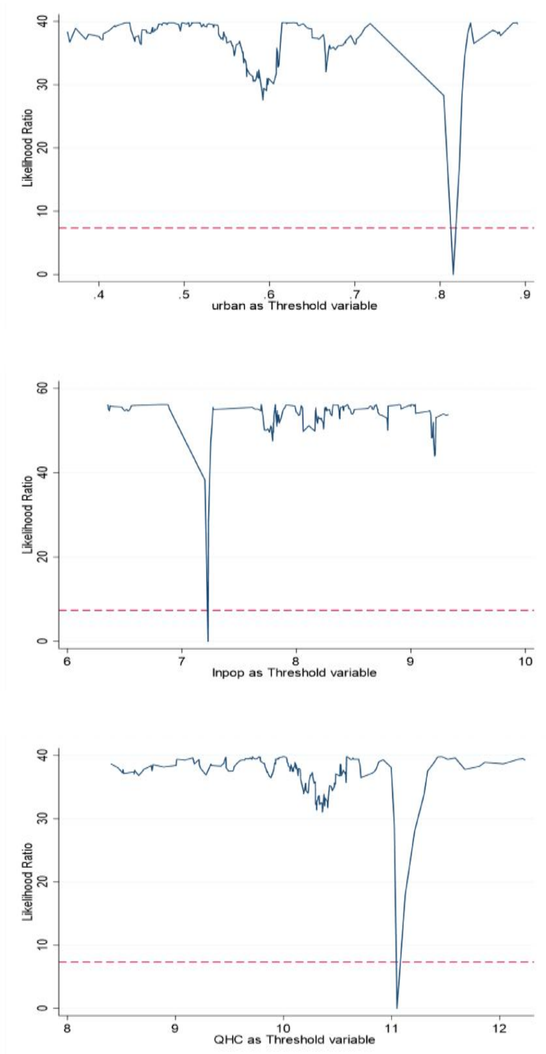

Figure 6. Regression diagram of threshold.

5.3.2 Regression analysis of threshold

From the perspective of population flow, as depicted in column 2 of Table 7, two scenarios emerge. (1) When the urbanization rate is below 0.8155, the impact of digitalization on environmental efficiency is minor, with a marginal increase of 0.15 for each unit of digitalization. This subdued effect may stem from the delayed impact of regional talent concentration, where the positive influence of economic development on environmental efficiency remains latent in the initial stages of urbanization. (2) Conversely, when the urbanization rate exceeds 0.8155, the positive effect of digitalization on environmental efficiency significantly intensifies, with a notable increase of 0.5 for every unit. Here, the knowledge spillover effect from talent concentration spurred by urbanization and the heightened environmental demand due to economic growth in later urbanization stages substantially enhance the environmental efficiency gains from the relocation of polluting industries to adjacent areas. The population concentration's scale effect pales in comparison to the efficiency gains in resource utilization it brings.

Considering population size, as revealed in column 3 of Table 7, two scenarios emerge. (1) When the population size is small, below 7.2284, digitalization exhibits a significant negative impact on environmental efficiency. This could be attributed to the limited effectiveness of digitalization in enhancing environmental efficiency at low population levels, offsetting the environmental impact of population growth, and possibly due to the reliance of digitalization on technological innovation rooted in knowledge and talent reserves, which are scarce in small populations. (2) Conversely, when the population size surpasses the threshold value of 7.2284, the spillover effect of digitalization on environmental efficiency demonstrates a nonlinear characteristic, with a substantial and positive marginal effect. The economies of scale arising from technological advancement through population growth sufficiently counterbalance the population size effect. Moreover, the increasing population density continually necessitates adaptive changes in urban functions, industrial structures, and spatial layout, fostering a positive relationship between population size and technological innovation. Digitalization, empowered by a rich talent pool and enhanced technological research and development, plays a pivotal role in improving environmental efficiency.

Examining population quality, as evident in column 4 of Table 7, two scenarios emerge. (1) When the quality of human capital is below 11.0497, digitalization significantly enhances environmental efficiency. However, the scope for promoting environmental awareness and consumption capacity is limited, hindering improvements in environmental efficiency through consumption structure upgrades. Additionally, concerning educational attainment, digitalization's impact on employment in non-ICT sectors and its influence on higher education groups in software and other high-tech industries are steadily increasing over time. (2) Conversely, when the quality of human capital surpasses 11.0497, digitalization continues to play a significant role in enhancing environmental efficiency. Here, the accumulated quality of human capital becomes pivotal, with higher educational levels associated with greater environmental consciousness. Demand incentives for green innovation, coupled with strategic enterprise intelligence, and enhanced technology absorption capacity, contribute to the overall improvement in environmental efficiency.

Table 7. Regression results.

		(1) EE		(2) EE		(3) EE
Dig×I	Urban≤0.8155	0.150*** (5.311)	Lnpop≤7.2284	-0.266*** (-4.076)	Qhc≤11.0497	0.141*** (4.610)
	Urban>0.8155	0.500*** (8.493)	Lnpop>7.2284	0.132*** (2.854)	Qhc>11.0497	0.249*** (5.800)
_cons		2.504*** (4.770)		0.540*** (6.779)		2.105*** (3.750)
Control variables		YES		YES		YES
N		240		240		240
R2		0.337		0.343		0.213

5.4. Mediating Effect Analysis of Institutional Factors

Amidst the era of digitalization and high-quality economic development, the issue of tax structure mismatch stands out prominently, calling for tax systems to adapt to the ongoing transformation of the digital economy (Huang et al., 2021). Digitalization heralds tax collection and administration reforms, leveraging information technology to optimize collection methods (Bai et al., 2021), thereby achieving more efficient tax management and enhancing the quality of government revenue information. Consequently, this paper examines whether tax structure, fiscal revenue quality, and the allocation of education expenditure serve as mediating mechanism variables influencing the impact of digitalization on environmental efficiency.

Model (2) reveals that digitalization has a significantly positive impact on the tax proportion at the 1% significance level. The positive influence of digitization and the intelligent upgrading of tax collection management on the quality of fiscal revenue outweighs the challenges posed by digitalization, such as tax base erosion and mismatch. The “tax administration by number” reform has yielded remarkable results. Fiscal revenue quality (tax proportion) is linked to regional economic growth and structure, as well as tax collection management levels, thereby promoting environmental efficiency.

Model (3) indicates that digitalization has a significantly negative impact on local education expenditure. On one hand, digitalization development fosters online education and other smart education modalities to mitigate educational resource disparities. On the other hand, digitalization development exacerbates the demand for knowledge talent, potentially leading to a crowding-out effect on local government subsidies, such as R&D spending for enterprises. Local education expenditure positively affects environmental efficiency by enhancing human capital quality, yet it may also crowd out environmental protection investments.

Model (4) demonstrates that digitalization has a significantly positive impact on tax structure. Rapid digitalization development highlights tax structure issues, prompting tax structure reform. Digitalization-optimized tax structures encompass tax structure, tax burden distribution, and collection and management. A substantial share of direct tax in fiscal revenue suggests that taxation fosters a more equitable society. Increased disposable income for residents and reduced consumption costs may positively impact environmental efficiency by stimulating environmental demand.

Table 8. Results of mediation effect.

	(1) EE	(2) R_tax	(3) Edu_exp	(4) S_tax
Dig	0.135***	0.207***	-0.043*	0.325**
	(3.076)	(2.809)	(-1.840)	(2.121)
Lnfdi	0.003	0.000	0.001	-0.015
	(0.840)	(0.064)	(0.589)	(-1.270)
Lnpop	-0.208***	-0.370***	0.155***	-0.008
	(-2.666)	(-2.826)	(3.721)	(-0.030)
Lnfbr	0.022	-0.082***	-0.033***	0.196***
	(1.577)	(-3.539)	(-4.493)	(4.094)
pGDP_g	0.060*	0.037	-0.089***	0.316***
	(1.744)	(0.640)	(-4.875)	(2.662)
_cons	2.161***	4.340***	-0.840***	-0.808
	(3.586)	(4.296)	(-2.618)	(-0.385)
N	240	240	240	240
R2	0.179	0.215	0.276	0.397

6. Robustness Test

6.1 Replacing explained variables

In this paper, the energy consumption structure and provincial carbon emissions are taken as alternative variables of environmental efficiency to estimate the model again. The impact of digitalization on energy consumption structure (shown in the column 2) and provincial carbon emissions (shown in the column 3) is significantly negative, indicating the robustness of the benchmark regression results.

Table 9. Robustness test.

	(1) EE	(2) Ecs	(3) lncarb
Dig	0.119**	-0.468***	-0.646***
	(2.221)	(-3.280)	(-3.241)
_cons	2.167***	1.705	-3.103
	(3.306)	(0.975)	(-1.270)
Control variables	YES	YES	YES
N	240	240	240
R2	0.206	0.263	0.232

6.2 Replacing estimation model

To address endogeneity concerns, we employ the dynamic panel GMM model for robustness testing. This approach introduces the lag of the dependent variable as an explanatory variable and utilizes FDI and fiscal revenue as instrumental variables. Both the lagged environmental efficiency and digitalization variables exhibit significant positive coefficients. The AR(1) test yields a p-value of 0.000, and the Sargan test produces a p-value of 0.112, indicating the validity of the instrumental variables and reaffirming the robustness of the results.

Table 10. Robustness test results of replacing the estimation model.

	(1) EE
L.EE	0.470***
	(6.064)
Dig	0.150***
	(3.684)
Control variable	YES
N	180

7. Heterogeneity analysis based on resource endowment

The regression results reveal a positive coefficient for digitalization itself, along with a significantly positive cross-sectional term between digitalization and whether the province is resource-based, indicating a noteworthy moderating effect. Specifically, the positive influence of digitalization on environmental efficiency is amplified in resource-based regions. In provinces without significant resource dependence, the increase in environmental efficiency is 0.095 units per incremental level of digitalization. However, in resource-rich provinces, this figure rises to 0.135 units higher than non-resource-based areas. This suggests that digitalization contributes more robustly to environmental efficiency in regions abundant in resources compared to others, highlighting significant heterogeneity in resource endowment's impact on the relationship between digitalization and environmental efficiency.

This phenomenon may be attributed to the heightened degree to which digitalization bolsters environmental efficiency, as resource-rich regions possess greater leeway to enhance their environmental standards. Additionally, stringent environmental regulations may drive more aggressive green innovation in industries facing high environmental risks, both in terms of quantity and quality (Wang et al., 2021).

Table 11. Moderating effect analysis of resource-based provinces.

	(1) EE	(2) EE	(3) EE
*D*Dig*	0.131**	0.118**	0.135***
	(2.526)	(2.288)	(2.630)
Dig	0.100***	0.103**	0.095**
	(3.777)	(2.236)	(2.092)
Lnfdi		0.003	0.002
		(0.853)	(0.448)
Lnpop		-0.153**	-0.218***
		(-2.033)	(-2.852)
Lnfbr		0.012	0.020
		(0.925)	(1.485)
Lntrade			0.016**
			(2.500)
pGDP_g			0.080**
			(2.356)
_cons	0.635***	1.790***	2.163***
	(123.734)	(3.039)	(3.670)
N	240	240	240
R2	0.165	0.188	0.231

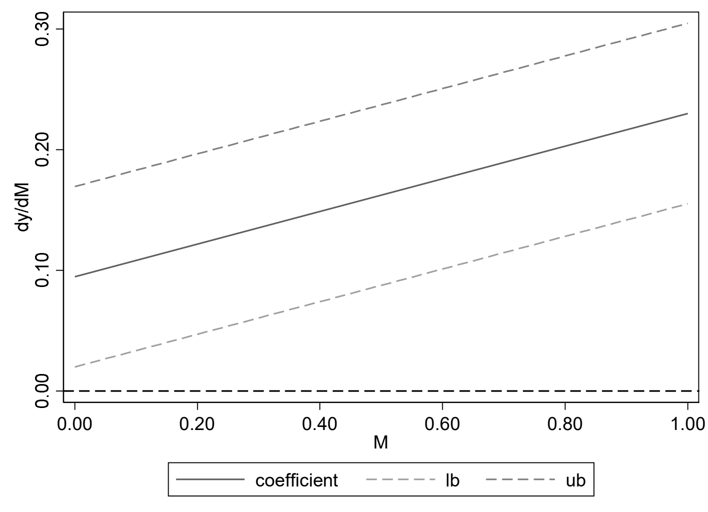

Figure 7. Results of moderating effect.

Some estimates of the moderating effects reported in this paper are visualized graphically, $\hat{\beta}_{\text{Dig}} + \hat{\beta}_{\text{interact}} \times M_{\max}$ $\hat{\beta}_{\text{Dig}} + \hat{\beta}_{\text{interact}} \times M_{\min}$, etc. In the Fig.7, the solid line shows the estimated causal effect, and the dashed line shows the confidence interval at 90% confidence level, which shows the causal effect of digitalization on EE is always positive and statistically significant. The β_{Digl} and β_{interact} are greater than 0, indicating that the moderating effect reinforces the original positive effect.

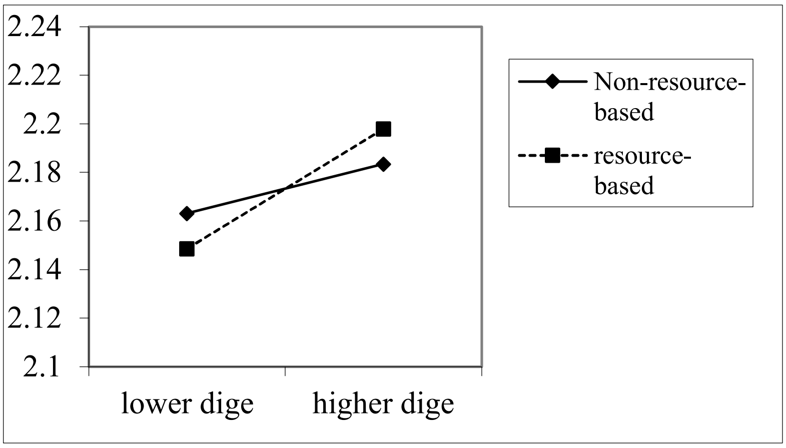

Figure 8. Interaction model between digitalization and resource endowment.

According to Figure 8, positive slope of the curve indicates that digitalization level has a positive effect on environmental efficiency. A large slope of the curve in resource-based areas indicates digitalization has stronger positive effect on EE in resource-based areas. In contrast, digitalization has a weaker effect on environmental efficiency within non-resource type areas. Resource endowment plays a moderating role in the digitalization promoting environmental efficiency.

8. Conclusions and implications

This study utilizes panel data encompassing 30 Chinese provinces spanning the years 2011 to 2018. It employs the entropy method to gauge the comprehensive index of digitalization and the SBM-DEA model, accounting for undesired output, to measure environmental efficiency, thereby analyzing their dynamic evolutions. Through the lenses of population and institutional factors, the study empirically investigates nonlinear characteristics and mechanisms using threshold and mediation models. The findings suggest several key points. First, digitalization significantly enhances environmental efficiency with notable “stage” heterogeneity. Overall, both digitalization (Dig) and environmental efficiency (EE) levels are on the rise, accompanied by regional dispersion expansion, demonstrating a “polarization” characteristic. Second, as the population structure optimizes and human capital improves, digitalization exhibits a nonlinear spillover effect with an increasing “marginal effect” (sharp “marginal increase” trend) on environmental efficiency. Third, digitalization influences environmental efficiency through fiscal revenue quality (tax proportion), education expenditure proportion, and tax system structure. Tax system reform can synergize with digitalization to bolster environmental efficiency improvement. Fourth, resource endowment significantly impacts digitalization's promotion of environmental efficiency, with resource-rich regions experiencing a robust positive effect on EE.

Furthermore, this paper offers several policy implications. Firstly, it advocates maximizing the driving impact of digitalization on environmental efficiency. Given the disparities in environmental efficiency and digital province economic development levels, fostering a spatially coordinated development pattern centered around provinces with agglomeration effects can enhance resource allocation and utilization efficiency. Strengthening technological innovation capabilities and leveraging their radiating and driving potential can further elevate overall environmental efficiency. Secondly, recognizing the strong positive impact of internal demographic factors in nonlinear spillover effects, the paper suggests optimizing population structure and expanding population size to maximize digitalization's enhancement effect on environmental efficiency. Accelerating urbanization construction and increasing investment in human capital can capitalize on the ecological environment improvements brought about by talent agglomeration and industrial transfer. Thirdly, the paper emphasizes harnessing technological progress and leveraging the role of the tax system to promote tax reform. Gradually increasing the proportion of direct taxes and refining the tax system to evolve into a more advanced and functionally complete structure can drive environmental regulation and institutional quality, fostering competition-driven green development and technological advancements. Additionally, resource-based provinces should bolster regional economic resilience through digitalization development, optimizing economic structures to attract labor inflows and enhance environmental efficiency through talent agglomeration effects.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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