

Article

How Does Digital Intelligence Transformation Reshape Carbon Emission Efficiency in Resource-Based Cities?

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Abstract

Resource-based cities face persistent challenges in reconciling economic growth with the transition to low-carbon development. This tension poses significant obstacles to sustainable regional development. Digital intelligence transformation (DIT) refers to the deep integration of digitalization and intelligent technologies. It offers a new pathway to enhance urban sustainability. Using panel data from 110 Chinese resource-based cities from 2013 to 2022, this study examines the impact of DIT on carbon emission efficiency (CEE). A comprehensive DIT index is constructed, and the SBM-GML approach is applied to measure CEE. A two-way fixed-effects model is employed to estimate the impact of DIT on CEE. The results show that DIT significantly improves CEE. A one-standard-deviation increase in DIT is associated with a 0.033 rise in CEE, which equals 3.96% of the sample mean. Mechanism analysis indicates that this effect is closely linked to lower resource misallocation and stronger green technological innovation. Heterogeneity analysis further suggests that DIT has a stronger impact in cities with advanced green finance, better digital infrastructure, and those at mature or regenerative development stages. Overall, the findings provide robust empirical evidence that digital intelligence technologies can serve as an effective driver of sustainable development in resource-based cities.

Keywords: digital intelligence transformation; resource-based cities; carbon emission efficiency; resource misallocation; green technological innovation

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1. Introduction

Amid the growing frequency of extreme weather events, carbon emissions—the primary driver of climate change—have emerged as a global challenge with profound implications for human well-being [1,2]. Although low-carbon development has gained broad international recognition, achieving Goal 13 (Climate Action) of the UN 2030 Agenda requires more than policy commitments; it also requires substantial improvements in production efficiency [3]. Carbon emission efficiency (CEE) measures economic output per unit of carbon emissions, taking input factors into account. It is widely used to assess the decoupling of economic growth from carbon emissions. Under growing resource and environmental constraints, improving CEE has become essential for countries seeking sustainable development.

As the world's second-largest economy, China faces the dual challenge of maintaining economic growth while meeting its "dual-carbon" targets—namely, peaking carbon emissions by 2030 and achieving carbon neutrality by 2060 [4]. China's rapid growth has long depended on non-renewable resource consumption, leading to significant environmental externalities [5]. This challenge is particularly pronounced in resource-based cities, which account for 43.6% of all Chinese cities and serve as major energy supply centers [6]. Due to their prolonged reliance on resource extraction and factor-intensive industries, these cities often face high-carbon lock-in, resource depletion, and low production efficiency. Therefore, improving CEE in resource-based cities is not only an environmental necessity but also a critical condition for their long-term economic viability.

Against this backdrop, digital intelligence transformation (DIT) has become an important force driving technological change. According to the *China Digital Economy Development Research Report* (2024) published by the China Academy of Information and Communications Technology (CAICT), China's digital economy reached 53.9 trillion yuan in 2023, accounting for 42.8% of GDP (https://www.caict.ac.cn/kxyj/qwfb/bps/202408/t20240827_491581.htm, accessed on 29 January 2026). As digitalization becomes a dominant development paradigm, the Chinese government has launched a series of urban initiatives centered on DIT [7]. DIT represents an advanced stage of digital development characterized by the deep integration of digital technologies and intelligent systems [8,9]. By integrating data analytics and algorithmic decision-making into production and governance, DIT enhances adaptability and operational efficiency in complex urban systems [10]. Accordingly, it has been increasingly recognized as a potential pathway to promoting sustainable development in China [11–13].

While the role of DIT in promoting economic growth is widely recognized [14–16], its environmental effects are far from conclusive. Some studies suggest that DIT contributes to green development through mechanisms such as strengthening urban innovation capacity [17,18]. In contrast, other studies report that DIT may increase carbon emissions by requiring additional energy-intensive infrastructure [9,19]. These mixed findings are also evident in research on resource-based cities. Heterogeneity analyses indicate that DIT significantly promotes carbon reduction in resource-based cities, but not in non-resource-based cities [20]. Other studies find that its impact on carbon reduction is significant in non-resource-based cities but insignificant in resource-based cities [13]. Despite these contributions, the specific link between DIT and CEE in resource-based cities remains under-examined. To address this gap, this study focuses on three key questions. First, can DIT effectively improve CEE in resource-based cities? Second, through which mechanisms does DIT influence CEE in these cities? Third, how does this effect vary under different conditions within resource-based cities?

This study contributes to the literature in three ways. First, it focuses on resource-based cities and examines how DIT affects CEE. Previous studies have examined DIT's impact on carbon emissions, but its effects on environmental efficiency remain contested. Moreover, resource-based cities, where sustainability transitions are especially urgent, have received limited attention. To address this gap, we use panel data for 110 Chinese resource-based cities over the period 2013–2022 to examine the impact of DIT on CEE. This enriches the literature on environmental efficiency in resource-based cities and provides insights for sustainable development in China and other developing economies. Second, the study investigates the mechanisms through which DIT improves CEE, identifying two primary pathways: reducing resource misallocation and promoting green technological innovation. This examination establishes a theoretical foundation and offers practical guidance for designing targeted, DIT-enabled policies to enhance efficiency and incentives. Third, we conduct heterogeneity analyses based on green finance development, digital infrastructure, and the type of resource-based city. The results show that

DIT's positive effect on CEE is stronger in cities with well-developed green finance, advanced digital infrastructure, and those at mature or regenerative stages of development. These findings offer a nuanced understanding of DIT's impact and provide empirical support for tailored local policies to promote sustainable development in resource-based cities.

The remainder of this study is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the theoretical framework. Section 4 introduces the research methodology. Section 5 reports the empirical results. Finally, Section 6 concludes with policy implications, limitations, and directions for future research.

2. Literature Review

2.1. Carbon Emission Efficiency (CEE) Estimation and Drivers

CEE evaluates carbon performance from both economic efficiency and low-carbon development perspectives and can be measured using different methodological approaches [21]. It is typically assessed using two approaches: single-factor and total-factor methods. Single-factor CEE typically reflects the ratio of carbon emissions to economic output, using indicators such as carbon productivity or carbon emission intensity [1]. While straightforward and easy to apply, this approach overlooks the multiple input factors involved in production and fails to account for substitution effects among inputs [22]. In contrast, total-factor CEE considers efficiency from a comprehensive input-output perspective. It captures the ability to increase economic output while reducing carbon emissions, accounting for three key inputs: capital, labor, and energy consumption [23]. Total-factor CEE can be estimated using parametric or non-parametric methods. Parametric methods, such as Stochastic Frontier Analysis (SFA), require a predefined functional form [24,25]. Non-parametric methods, exemplified by Data Envelopment Analysis (DEA), do not require specifying a functional form, avoiding subjective parameter weighting [26]. Building on DEA, more advanced techniques such as the Directional Distance Function (DDF) and the Slacks-Based Measure (SBM) have been developed [8]. Among these methods, SBM is widely used in empirical CEE studies. This is because it can incorporate undesirable outputs and handle non-radial, non-oriented efficiency measurement. Accordingly, this study employs the SBM model and integrates it with the globally benchmarked Malmquist–Luenberger index to construct the SBM-GML model. This approach effectively captures the dynamic evolution of CEE in resource-based cities and provides a reliable dependent variable for subsequent empirical analysis.

Numerous studies examine the socio-economic drivers of CEE. Empirical studies have focused primarily on regional and industrial scales. At the regional level, investigations have been conducted at national [27], provincial [1], municipal [28], and enterprise scales [29]. At the industry level, research has targeted sectors such as manufacturing [24], energy [30], services [31], and transportation [32]. These studies have identified a range of factors influencing CEE, including technological innovation [33], resource misallocation [34], agriculture [35], and the digital economy [36], among others. Together, this literature has advanced the understanding of CEE and established a solid theoretical foundation for this study to investigate how DIT affects CEE in resource-based cities.

2.2. The Evolution of Digital Intelligence Transformation (DIT)

The concept of “digital intelligence” was first proposed in a 2015 report by the Zhiben Foundation at Peking University. It was defined as the integration of digital intellectualization and intelligent digitalization. Subsequent research has broadened its conceptual scope. Interpretations of DIT generally fall into two perspectives. The first views DIT as the integrated application of various information technologies [37]. For example, Xue and

Chen (2024) describe digital intelligence as a framework encompassing artificial intelligence, big data, blockchain, the Internet, and cloud computing [38]. The second perspective regards DIT as the close integration of digitalization and intelligence [18,39–42]. Studies adopting this view emphasize that DIT represents a new stage in the evolution of the digital economy [8,19,20,43]. Given its widespread adoption in the literature, this study adopts the second perspective, which defines DIT as the integration of digitalization and intelligence. This perspective serves as the conceptual foundation of this study and provides a clear basis for constructing a measurable DIT index along two dimensions: digitalization and intelligence.

Three main approaches are used to measure DIT. The first is the questionnaire survey method, which assesses DIT levels based on responses to targeted surveys [9,44]. The second is the text extraction method, which applies Python 3.9 to extract DIT-related keywords from corporate annual reports, using keyword frequency as a proxy for DIT [42,45]. The third is the comprehensive index method, which develops a DIT index based on digitalization and intelligence and computes scores using entropy weighting or principal component analysis [19,40,46]. Compared with the first two approaches, the comprehensive index method offers a more systematic and thorough assessment, better capturing both the depth and breadth of a city's DIT.

2.3. *The Nexus of DIT and CEE*

To date, five studies are closely related to the present research. Four of these report that DIT contributes to improving CEE. Guo and Xu (2025) find that DIT significantly reduces carbon emission intensity overall, although heterogeneity analyses show the effect is insignificant in resource-based cities [13]. Cao et al. (2024) demonstrate that DIT lowers carbon emissions through improvements in labor productivity and accelerated capital renewal [10]. Chen et al. (2025) show that increases in digital intelligence-related patents improve CEE by reducing energy consumption, optimizing the energy mix, and lowering energy intensity [8]. Li et al. (2024) report that digital intelligence promotes coordination between pollution control and carbon reduction, with heterogeneity analyses confirming this effect in resource-based cities [20]. In contrast, one study presents a divergent finding, indicating a U-shaped relationship between DIT and carbon emission intensity [19]. Overall, empirical research on the relationship between DIT and CEE remains limited and inconclusive. Accordingly, this study focuses on resource-based cities to provide a more rigorous assessment of the impact of DIT on CEE.

2.4. *Literature Gaps*

The studies reviewed above provide important insights into the relationship between DIT and CEE. Nevertheless, three major gaps remain.

First, although some research has examined the heterogeneous effects of DIT on CEE between resource-based and non-resource-based cities, findings are still inconsistent. In particular, research explicitly focusing on resource-based cities remains scarce. More importantly, most prior research measures the impact of digital intelligence using single-factor CEE, whereas relatively few studies adopt a total-factor framework that captures efficiency changes more comprehensively. To address these limitations, this study focuses on resource-based cities, constructs an integrated DIT index, and applies the SBM-GML method to calculate total-factor CEE. This allows for a more rigorous assessment of the DIT–CEE relationship.

Second, although several studies have explored selected channels through which DIT may affect CEE—such as capital renewal and energy intensity—systematic evidence on key structural mechanisms remains limited. In particular, the roles of resource misallocation and green technological innovation have received insufficient attention, despite their

theoretical importance in resource-dependent regions. To address this gap, this study examines these two pathways to clarify how DIT influences CEE in resource-based cities. The analysis provides insights with clear theoretical and policy relevance.

Third, the heterogeneous impacts of DIT on CEE across different contextual conditions are still underexplored. Limited attention has been paid to how digital infrastructure, green finance development, and different types of resource-based cities shape the effectiveness of DIT. To fill this gap, this study investigates these dimensions to reveal how DIT's efficiency-enhancing effects vary across different scenarios. The empirical evidence provides a scientific basis for differentiated policy design and targeted management strategies tailored to resource-based cities.

3. Theoretical Analysis

3.1. *The Impact of DIT on CEE*

Economic growth in resource-based cities has historically depended on natural resource extraction, often resulting in resource-intensive development, high energy consumption, and severe pollution. DIT, driven by data and enabled by intelligent technologies, provides new opportunities to improve efficiency in these cities.

First, DIT elevates data to a core production factor. Industrial Internet platforms integrate end-to-end information on resource extraction, energy use, and carbon emissions, creating a real-time “resource-data-value” cycle [4,47]. By leveraging data assets to reduce energy inputs [48], DIT accelerates the structural adjustment of production factors [49] and mitigates the pollution externalities of resource exploitation. As a result, the carbon emission efficiency of resource-based cities is enhanced through both energy savings and reduced emissions.

Second, focusing on intelligent technologies, DIT uses advanced data analytics and dynamic algorithms to monitor market changes in real time [50]. This enables accurate forecasting and optimization for energy firms and regulators [51–53]. Improved decision-making accuracy allows resources to be allocated more efficiently, thereby reducing energy waste and carbon emissions [54–56]. At the same time, AI automates repetitive, low-skill tasks on production floors. When combined with real-time monitoring and predictive diagnostics, AI enables proactive fault detection and resolution, reducing labor costs and downtime [57]. These improvements further enhance CEE in resource-based cities.

Furthermore, DIT encourages public participation in environmental governance. Platforms such as “Carbon Achiever” (China's Tan Daren) convert green behaviors into tradable digital assets, while apps like “Eco Snapshot” (China's Huanbao Suishoupai) use AI recognition and geolocation technologies to shorten response times to pollution events [58]. Large-scale public oversight creates network effects, prompting governments and firms to respond more quickly to environmental issues. In this way, individual green actions aggregate into a city-wide emission reduction force, further improving CEE.

Hypothesis 1. *DIT can effectively enhance CEE in resource-based cities.*

3.2. *The Associational Mechanism of Resource Misallocation*

Resource misallocation in resource-based cities occurs when capital, labor, and other inputs remain locked in traditional, high-pollution, and low-efficiency sectors, thereby crowding out resources for emerging eco-friendly industries [59]. Such misallocation limits eco-oriented industrial upgrading and increases the economic cost of low-carbon transitions. Consequently, resource misallocation is generally negatively associated with CEE in these cities [60].

First, DIT enables intelligent decision-making in resource allocation. Through digital monitoring and advanced analysis of production and consumption, governments and

firms can design more precise resource-planning and management strategies. This optimizes the allocation of production factors and enhances CEE [61]. Second, DIT improves the alignment of supply and demand, reducing resource waste during production. Overproduction is mitigated through big data- and AI-driven demand forecasting. At the same time, losses of raw materials, energy, and inventory are minimized through IoT- and AI-enabled smart scheduling and flexible production [62,63]. These measures enhance resource-use efficiency, alleviate misallocation, and further improve CEE. Third, DIT reduces information barriers, enabling broader and more efficient resource allocation. Digital intelligence technologies reduce transaction costs and information asymmetry [64,65]. This creates transparent channels that direct capital, talent, and other resources toward low-carbon and high-efficiency projects. This accelerates the phase-out of outdated capacity. Moreover, digital platforms transcend geographical boundaries, facilitate the redeployment of idle resources, and improve the utilization of existing assets [59]. These effects further enhance CEE.

Hypothesis 2. *DIT is associated with higher CEE in resource-based cities through reduced resource misallocation.*

3.3. The Associational Mechanism of Green Technological Innovation

Green technological innovation is a key driver for reducing carbon emissions and improving efficiency [66,67]. By promoting the green upgrading of industries and enhancing energy efficiency, it supports sustained improvements in CEE in resource-based cities [68].

First, DIT strengthens green innovation through virtualized R&D. Virtual experiments substitute for physical testing and reshape traditional R&D models. They also enable intelligent screening and support data-driven innovation. This reduces trial-and-error costs and development time [69], accelerates green technological breakthroughs [70,71], and consequently enhances CEE in resource-based cities. Second, DIT integrates green innovation systems across multiple levels. At the inter-firm level, supply chain collaboration platforms break down data silos between upstream and downstream firms, facilitating joint green R&D [72,73]. At the government–firm level, digital government platforms dynamically aggregate corporate demands and policy resources, while AI algorithms match subsidies to recipients in real time [74]. These processes improve the effectiveness of green technological innovation, further boosting CEE. Third, DIT fosters an open innovation ecosystem by integrating cross-boundary knowledge. Digital platforms connect firms, universities, and research institutes into an integrated “industry-academia-research-application” network [75]. Tacit knowledge is codified and widely disseminated, creating a co-creating and co-sharing innovation community [76]. Rapid circulation of green innovation knowledge facilitates technology diffusion, enhances green innovation, and improves CEE in resource-based cities.

Hypothesis 3. *DIT is positively associated with CEE in resource-based cities through enhanced green technological innovation.*

To synthesize the theoretical mechanisms discussed above into an integrated conceptual framework, we propose a mechanism framework depicted in Figure 1. This framework posits that DIT enhances CEE in resource-based cities primarily through two parallel mediating channels. Path 1 (The Upper Route in Figure 1): DIT facilitates intelligent decision-making, improves supply-demand matching, and reduces information barriers. These functionalities collectively contribute to reducing resource misallocation, thereby

leading to improved CEE. This path corresponds to the theoretical foundation of Hypothesis 2. Path 2 (The Lower Route in Figure 1): DIT enables virtualized R&D, integrates multi-level innovation systems, and fosters open innovation ecosystems. These capabilities work in concert to improve green technological innovation, which in turn promotes CEE. This path formalizes the logic underlying Hypothesis 3. The framework integrates these two complementary pathways and illustrates how DIT advances CEE in resource-based cities.

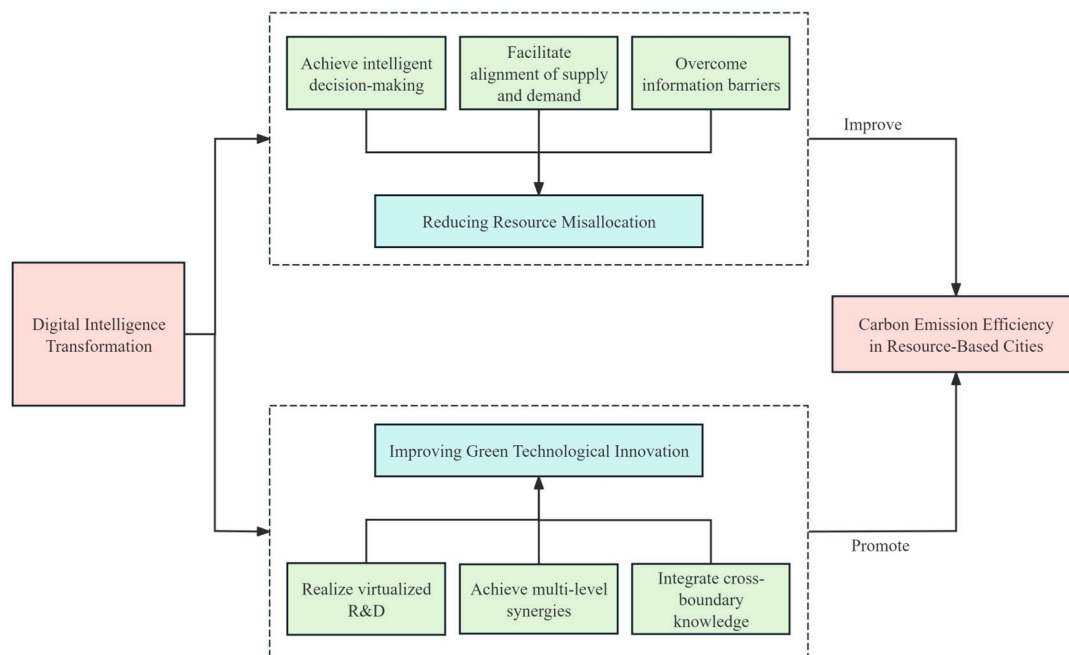


Figure 1. Mechanism framework. (Arrows indicate the direction of influence. The pink boxes represent core variables, the blue boxes denote mediating mechanisms, and the green boxes indicate specific functional channels. The dashed boxes illustrate grouped mechanisms.).

4. Methodology

4.1. Model

4.1.1. Baseline Regression Model

We employ a two-way fixed-effects model to examine the effect of DIT on CEE in resource-based cities. Urban-level controls are used to capture city-specific characteristics. In addition, city and year fixed effects are incorporated to control for unobserved heterogeneity and time-varying shocks. Following Zeng and Zhang (2024), the baseline model is given by [77]

$$Cee_{it} = \beta_0 + \beta_1 Dit_{it} + \theta X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

where Cee_{it} represents the carbon emission efficiency of resource-based city i in year t ; Dit_{it} stands for the degree of digital intelligence transformation; and X_{it} is a group of control variables. μ_i and φ_t represent city and year fixed effects, correspondingly. ε_{it} is the stochastic error term, and β_0 is the constant term. β_1 and θ are the regression coefficients to be estimated. The coefficient of primary interest is β_1 ; a significantly positive estimate of β_1 would indicate that DIT enhances CEE in resource-based cities.

4.1.2. Associational Mechanism Model

Our prior theoretical discussion implies that DIT can boost CEE in resource-based cities by alleviating resource misallocation and fostering green technological innovation. Following He et al. (2020), we employ the below model to examine the underlying mechanisms [78]:

$$M_{it} = \beta_0 + \beta_1 Dit_{it} + \theta X_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (2)$$

where M_{it} denotes the mechanism variables, namely resource misallocation (Rm) and green technological innovation (Gti). All remaining variables are defined consistently with Equation (1).

4.2. Variables

4.2.1. Dependent Variable

Carbon emission efficiency (Cee). Following Ding et al. (2025), the CEE of resource-based cities is quantified by combining the SBM model with the global Malmquist–Luenberger (GML) productivity index [1]. The non-radial, non-oriented SBM model accounts for undesirable outputs and evaluates the relative efficiency of decision-making units (DMUs) along the production frontier [79,80]. Compared with traditional radial DEA models, SBM performs better, especially under variable returns to scale (VRS) conditions [81]. The GML index is constructed using global benchmark technology [82]. This improves the comparability of technical efficiency across DMUs relative to the conventional Malmquist–Luenberger index. As the GML index captures productivity changes between consecutive periods, CEE is computed as the cumulative product of sequential GML indices. Detailed derivations and calculation procedures are reported in Appendix A.

To ensure intertemporal comparability of efficiency levels, the empirical panel covers the period 2013–2022, while the CEE series is anchored to 2011 as the base year. The year 2011 marks the beginning of China’s 12th Five-Year Plan, during which carbon intensity reduction was formally incorporated as a mandatory national target, making it a theoretically and institutionally relevant benchmark for evaluating subsequent efficiency improvements. Using 2011 as a unified base year helps avoid distortions associated with normalizing efficiency at the sample start year and prevents efficiency changes from being mechanically driven by this choice. Consequently, the CEE value observed in 2013 reflects the cumulative productivity change from 2011 to 2013. This initialization strategy implies that cities entering the 2013 panel already embody efficiency trajectories accumulated over the pre-sample period (2011–2013). This is econometrically advantageous because it allows the analysis to account for heterogeneous initial efficiency levels rather than imposing a homogeneous starting point in 2013.

The SBM model uses three categories of variables: inputs, desirable outputs, and undesirable outputs [80]. Inputs include labor, capital, and energy. The outputs consist of GDP (desirable output) and carbon emissions (undesirable output) [30]. Labor is represented by the year-end number of employees. Capital is measured using the capital stock calculated via the perpetual inventory method, with 2011 as the base year [83]. Energy input is measured using electricity consumption, which is widely adopted in city-level studies due to its high data availability, consistent statistical definition across cities, and strong correlation with total final energy use, particularly in China’s industrial-oriented resource-based cities. In these cities, electricity-intensive sectors—such as mining, metallurgy, and heavy manufacturing—account for a substantial share of overall energy demand, making electricity consumption a reasonable proxy for aggregate energy input. The desirable output is real GDP, while the undesirable output is carbon emissions. Carbon

emissions data are obtained from the Emissions Database for Global Atmospheric Research (EDGAR), which provides spatially disaggregated and methodologically consistent estimates of emissions from energy combustion, industrial processes, and other anthropogenic sources [84]. Although energy input and carbon emissions are sourced from different datasets, they are conceptually consistent within the production framework: electricity consumption reflects the scale of energy services used in production, while EDGAR emissions capture the resulting carbon externalities. Using EDGAR data also helps mitigate underreporting and cross-city incomparability commonly associated with locally reported emission statistics.

We acknowledge that electricity consumption does not fully capture non-electric fossil energy use, which may introduce measurement error in the energy input variable. However, such measurement error is likely to be systematic rather than city-specific and therefore unlikely to bias relative efficiency comparisons across cities. If anything, the omission of non-electric energy inputs may lead to a conservative estimate of inefficiency, implying that the estimated positive effect of digital intelligence transformation on CEE is more likely to be understated than overstated.

4.2.2. Independent Variable

Digital intelligence transformation (*Dit*). DIT represents the deep integration of digitalization and intelligence. Digitalization provides the data foundation by converting physical and economic activities into standardized data that can be stored, processed, and transmitted at low cost. Intelligence further realizes the value of these data through advanced technologies such as perception, learning, reasoning, and decision-making, thereby enabling automated, adaptive, and continuously optimized production and governance processes. Together, digitalization and intelligence form a real-time closed-loop system that characterizes digital intelligence transformation. Following Jia et al. (2025) and Chen et al. (2025), a composite DIT index is constructed along two core dimensions: digitalization and intelligence [40,46].

Specifically, the digitalization dimension captures the extent to which data are generated, applied, and diffused within cities along four aspects. First, digital popularization, measured by internet users and mobile-phone users per 100 people, reflects the availability of basic digital infrastructure and residents' readiness for digital engagement. Second, digital application, proxied by the Peking University Digital Inclusive Finance Index, telecom revenue per capita, and e-commerce transaction volume, reflects the depth of digital technology adoption in economic and financial activities. Third, digital innovation, measured by the number of digital technology patent applications, captures cities' capacity to develop new digital solutions and technologies. Fourth, digital talent, proxied by the share of employees in computer services and software industries, reflects the human capital foundation necessary for developing, operating, and upgrading digital systems.

The intelligence dimension reflects cities' capacity to transform data into intelligent decision-making and technological upgrading and is assessed from two complementary aspects. First, intelligent foundation, measured by the number of AI enterprises and robot installation density, captures the physical and organizational infrastructure supporting artificial intelligence. Specifically, AI enterprises indicate the scale and maturity of the local intelligent technology ecosystem, while robot density directly reflects the deployment of automated and intelligent systems in production processes. Second, intelligent innovation, measured by the number of AI patent applications, captures cities' capabilities in advanced algorithms, such as machine learning and autonomous decision-making, thereby distinguishing genuine intelligent transformation from basic digitization.

Detailed indicators are provided in Table 1 and Appendix B. To reduce subjective bias in weighting and accurately capture the relative contribution of each indicator, the

entropy weight method is applied to measure the DIT level of China's resource-based cities [85]. The specific calculation steps are outlined in Appendix C.

Given the relatively higher weights assigned to certain indicators—such as the number of AI enterprises and e-commerce transaction volume—we further examine whether the composite DIT index is dominated by a small subset of high-weight indicators, which could mechanically drive the baseline results and undermine the interpretability of the composite measure. Specifically, we calculate the correlations between each individual indicator and the overall DIT index to assess their respective contributions. As reported in Appendix Table A1, all indicators exhibit positive and statistically significant correlations with the overall index, with correlation coefficients ranging from 0.419 to 0.765. Importantly, no single indicator exhibits an excessively dominant correlation. These findings confirm that the constructed DIT index captures a broad-based process of digital intelligence transformation rather than reflecting the influence of any specific indicator.

Table 1. Measurement index system of DIT.

First-Level Indicator	Second-Level Indicator	Third-Level Indicator	Indicator Type	Weights
Digitalization	Digital popularization	Internet users per 100 people	+	0.026
		Mobile-phone users per 100 people	+	0.026
	Digital application	Peking University Digital Inclusive Finance Index	+	0.031
		Telecom revenue per capita	+	0.028
		E-commerce transaction volume	+	0.197
	Digital innovation	Number of digital technology patent applications	+	0.180
	Digital talent	Share of computer services and software employees	+	0.028
Intelligence	Intelligent foundation	Number of AI enterprises	+	0.277
		Robot installation density	+	0.066
	Intelligent innovation	Number of AI patent applications	+	0.140

Note: “+” indicates a positive indicator (i.e., a higher value contributes positively to DIT).

4.2.3. Associational Mechanism Variables

Building on the framework of Hsieh and Klenow (2009), resource misallocation (Rm) is constructed based on distortions in capital and labor allocation [86]. In this framework, a higher Rm value indicates greater deviation of factor allocation from the efficient benchmark, implying that capital and labor are not allocated to their most productive uses. In the context of resource-based cities, elevated Rm values typically reflect structural rigidities, factor market frictions, and path dependence associated with resource extraction industries. These factors hinder the reallocation of resources toward more productive and cleaner sectors. Conversely, lower Rm values suggest more efficient factor allocation and smoother resource reallocation across firms and industries. The detailed calculation steps are provided in Appendix D.

Following Luo et al. (2024), green technological innovation (Gti) is measured by the number of green patent applications [87]. Green patents are identified based on the International Patent Classification (IPC) Green List released by the World Intellectual Property Organization (WIPO) in 2010 [73]. Patent applications include both invention and utility-model categories. To reduce skewness in the data, the natural logarithm of one plus the total number of green patents is used.

4.2.4. Control Variables

To address omitted-variable bias, five controls commonly linked to CEE are included [88]. Government intervention (Gov) is measured as the ratio of total fiscal spending to regional GDP. Population size (Pop) is represented by the year-end registered resident count. R&D input (Rd) is captured by government spending on science and technology.

Industrialization level (*Ind*) is defined as the share of industrial value added in GDP. Urbanization level (*Urb*) is calculated as the share of urban residents in the total population.

4.3. Data

The *National Plan for Sustainable Development of Resource-Based Cities (2013–2020)*, issued by the State Council of China, identifies 126 resource-based cities, autonomous prefectures, and regions. Due to data limitations, 16 jurisdictions with insufficient observations were excluded, including Yangquan, Laiwu, Guang'an, Bijie, Pu'er, Karamay, Daxing'anling Prefecture, Altay Prefecture, Yanbian Korean Autonomous Prefecture, Aba Tibetan and Qiang Autonomous Prefecture, Liangshan Yi Autonomous Prefecture, Qiannan Buyei and Miao Autonomous Prefecture, Qianxinan Buyei and Miao Autonomous Prefecture, Chuxiong Yi Autonomous Prefecture, Haixi Mongol and Tibetan Autonomous Prefecture, and Bayingolin Mongol Autonomous Prefecture. The final sample is a panel of 110 resource-based cities in China from 2013 to 2022. Data were mainly obtained from the *China Energy Statistical Yearbook*, *China City Statistical Yearbook*, and *China Statistical Yearbook*. Table 2 reports the descriptive statistics.

With respect to data completeness, missing values are extremely limited. Specifically, only the urbanization level (*Urb*) contains missing observations, involving seven city–year cells: Liaoyuan (2022); Sanmenxia (2017); Luoyang (2017); Hebi (2017); Huainan (2022); Fuxin (2022); and Qitaihe (2022). These missing observations account for a negligible share of the total sample and are not concentrated in any particular period or region. As *Urb* is a control variable rather than a core explanatory variable, the impact of missing observations on the main estimation results is expected to be minimal.

Table 2. Descriptive statistics.

Variables	Obs	Mean	Std.Dev	Min	Max
<i>Cee</i>	1100	0.830	0.213	0.133	1.891
<i>Dit</i>	1100	0.140	0.084	0.009	0.767
<i>Rm</i>	1100	0.283	0.143	0.003	0.9998
<i>Gti</i>	1100	4.633	1.227	0.000	7.883
<i>Gov</i>	1100	0.230	0.107	0.044	0.741
<i>Pop</i>	1100	3.660	2.470	0.440	12.390
<i>Rd</i>	1100	3.705	4.691	0.075	36.213
<i>Urb</i>	1100	0.557	0.131	0.181	0.960
<i>Ind</i>	1100	0.377	0.130	0.081	0.845

5. Results

5.1. Baseline Regression Results

The empirical analysis begins with pooled OLS and then sequentially adds year fixed effects, city fixed effects, and control variables to examine the relationship between DIT and CEE. Table 3 reports the baseline results. The coefficient on DIT is positive and statistically significant across all specifications, indicating that DIT improves CEE. In particular, column (4), which includes fixed effects and control variables, reports a coefficient of 0.391. This indicates that a one-unit increase in DIT is associated with a 0.391-unit increase in CEE. In standardized terms, a one-standard-deviation increase in DIT raises CEE by approximately 0.033, equivalent to 3.96% of the sample mean. The magnitude suggests that improvements in digital intelligence transformation are economically meaningful, thereby supporting Hypothesis 1.

Table 3. Baseline results.

Variables	(1) <i>Cee</i>	(2) <i>Cee</i>	(3) <i>Cee</i>	(4) <i>Cee</i>
<i>Dit</i>	0.325 *** (0.088)	0.615 *** (0.086)	0.465 *** (0.167)	0.391 ** (0.167)
<i>Gov</i>				−0.005 (0.114)
<i>Pop</i>				0.081 *** (0.030)
<i>Rd</i>				0.001 (0.001)
<i>Urb</i>				−0.055 (0.132)
<i>Ind</i>				0.196 *** (0.072)
Constant	0.784 *** (0.014)	0.744 *** (0.014)	0.765 *** (0.023)	0.433 *** (0.150)
City FE	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes
Observations	1100	1100	1100	1100
R ²	0.016	0.126	0.718	0.722

Note: Standard errors in (); *** and ** indicate significance at the 1% and 5% levels, respectively.

5.2. Robustness Tests

5.2.1. Instrument Variable Approach

To address potential endogeneity caused by omitted variables, the relationship between DIT and CEE is re-examined using an instrumental variable (IV) approach. Following Huang et al. (2025), the IV is constructed by multiplying the city's topographic undulation by the one-period lag of the logarithm of nationwide internet users [89]. This instrument meets the two key requirements for validity: relevance and exogeneity. Regarding relevance, topographic relief plays an important role in shaping the cost and feasibility of deploying DIT-related infrastructure. Cities with rugged terrain face higher construction costs and greater engineering complexity when building digital infrastructure—such as fiber-optic networks, 5G base stations, and data centers—due to natural constraints like mountains and unstable geological conditions. When combined with the nationwide expansion of internet usage, these geographic constraints become increasingly binding, limiting the extent to which cities can translate national digital trends into local DIT development. Regarding exogeneity, topographic relief is a predetermined and largely random geographic characteristic that is orthogonal to contemporaneous economic activities and environmental outcomes. Interacting this time-invariant geographic feature with lagged nationwide internet users further introduces exogenous temporal variation while mitigating concerns about reverse causality at the city level.

The two-stage least squares (2SLS) estimation results are presented in Table 4. The first-stage regression yields a negative and statistically significant coefficient on the IV, confirming its relevance. This negative sign is economically intuitive: cities with more complex terrain experience greater physical and economic barriers to digital infrastructure deployment, and these disadvantages are amplified during periods of rapid nationwide internet expansion, resulting in a slower pace of DIT adoption relative to flatter regions. Thus, the instrument effectively captures the suppressing effect of geographic barriers on DIT development in the context of a national digital wave. In the second stage, DIT exhibits a statistically significant positive effect on CEE in resource-based cities. The Kleibergen–Paap rk LM statistic rejects the null hypothesis of underidentification at the

1% significance level. The Kleibergen–Paap rk Wald F statistic equals 21.248, which exceeds the Stock–Yogo weak identification test’s critical value of 16.38 at the 10% maximal IV relative bias level [90]. These results suggest that the instrument is not weak. Overall, the IV estimates provide robust support for Hypothesis 1.

Table 4. Instrumental variable (IV) estimation results.

Variables	2SLS First	2SLS Second
	(1) <i>Dit</i>	(2) <i>Cee</i>
<i>IV</i>	−0.060 ***	
	−0.007	
<i>Dit</i>		2.658 ***
		−0.893
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen–Paap rk LM		15.753 ***
Kleibergen–Paap rk Wald F		21.248
Observations	1100	1100
R ²	0.892	−0.300

Note: Standard errors in (); *** indicates significance at the 1% level.

A potential concern is that topographic conditions may influence CEE through channels other than DIT, such as transportation costs, industrial structure, or urbanization patterns. Several features of the empirical design substantially mitigate this concern. First, city fixed effects absorb all time-invariant geographic characteristics, including any direct effects of terrain on long-run economic structure or production efficiency. Second, year fixed effects control for common shocks related to energy prices, technological progress, and macroeconomic fluctuations that may jointly affect CEE across cities. Third, key time-varying confounders—such as urbanization level and economic development—are explicitly controlled for in the baseline specification, thereby limiting alternative transmission channels. Importantly, identification does not rely on topographic conditions per se, but on the interaction between topographic undulation and lagged national internet users. Although terrain may influence long-term urban and industrial development, identification relies on cities’ differential ability to translate nationwide internet expansion into local DIT, conditional on geographic constraints.

5.2.2. Alternative Measures of Core Variables

To address potential measurement errors, alternative measures are adopted for the key variables [91]. First, CEE (*Cee_g*) is recalculated by including carbon, SO₂, industrial wastewater, and dust emissions as undesirable outputs. The regression models are then re-estimated. As shown in column (1) of Table 5, the coefficient of DIT remains significantly positive. Second, DIT (*Dit_p*) is recalculated using Principal Component Analysis (PCA). Column (2) of Table 5 reports that DIT remains positively and significantly associated with CEE. Finally, both CEE and DIT are replaced simultaneously. The results in column (3) of Table 5 confirm that DIT consistently enhances CEE in resource-based cities. Overall, these robustness checks provide strong empirical support for Hypothesis 1.

To test whether the DIT index is driven by high-weight indicators—specifically AI enterprises and e-commerce transaction volume—we construct two leave-one-out indices by separately excluding each of these two indicators and reapplying the entropy-weight method. As reported in columns (4) and (5) of Table 5, the estimated effects of DIT remain positive and statistically significant. Taken together with the PCA-based alternative

weighting scheme reported above, these results indicate that the baseline estimates are not driven by any single high-weight indicator and are robust to alternative weighting schemes and index constructions.

Table 5. Other robustness tests results.

Variables	(1) <i>Cee_g</i>	(2) <i>Cee</i>	(3) <i>Cee_g</i>	(4) <i>Cee</i>	(5) <i>Cee</i>	(6) <i>Cee</i>	(7) <i>Cee</i>	(8) <i>Cee</i>	(9) <i>Cee</i>
<i>Dit</i>	0.501 *					0.259 *	0.519 ***	0.414 *	0.411 **
	(0.257)					(0.139)	(0.156)	(0.226)	(0.166)
<i>Dit_p</i>		0.047 **	0.062 **						
		(0.020)	(0.030)						
<i>Dit_noAI</i>				0.521 ***					
				(0.158)					
<i>Dit_noEcom</i>					0.333 **				
					(0.166)				
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1100	1100	1100	1100	1100	1100	900	770	1093
R ²	0.687	0.722	0.687	0.723	0.721	0.726	0.743	0.777	0.721

Note: Standard errors in (); ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.2.3. Winsorization

To mitigate the influence of outliers, all continuous variables are winsorized at the 0.5% level on both tails [92]. Column (6) of Table 5 reveals that the coefficient on DIT remains positive and statistically significant, confirming the robustness of the baseline results.

5.2.4. One-Period Lag of DIT

To address potential reverse causality, the model is re-estimated using a one-period lag of DIT [93]. As shown in column (7) of Table 5, the coefficient of DIT remains positive and statistically significant, consistent with the baseline results.

5.2.5. Controlling for COVID-19 Effects

The COVID-19 pandemic disrupted social and economic activities on a large scale, potentially affecting the estimation results [85]. To address this, data from 2020 to 2022 are excluded, and the model is re-estimated. The results in column (8) of Table 5 show that the DIT coefficient remains significantly positive, further supporting the reliability of the benchmark findings.

5.2.6. Excluding Observations with Missing Values

As a robustness check, we re-estimate the baseline model after excluding all observations with missing values, without applying any interpolation or imputation procedures. As documented in Section 4.3, only seven city–year observations are affected by missing data. The estimation results, reported in column (9) of Table 5, show that the coefficient of DIT remains positive and statistically significant, with a magnitude comparable to the baseline estimates. This indicates that the main findings are not sensitive to the treatment of the limited missing data.

5.2.7. Accounting for Potential Spatial Dependence

Given potential spatial dependence across cities—arising from technology diffusion, supply chains, and policy spillovers—we estimate a spatial panel model as a robustness

check. Specifically, we employ a Spatial Durbin Model (SDM) with an inverse geographic distance matrix. The estimation results are reported in Appendix Table A2. The coefficient on DIT remains positive and statistically significant after accounting for spatial dependence, and the long-run direct effect of DIT is also significantly positive, consistent with the baseline results. In contrast, the estimated spatial spillover effects are statistically insignificant. These findings indicate that the main conclusions are not driven by unaccounted spatial dependence and that the impact of digital intelligence transformation on carbon emission efficiency operates primarily through local channels.

5.3. Associational Mechanism Analysis

5.3.1. Effect of Reducing Resource Misallocation

Resource misallocation refers to the suboptimal distribution of production factors, including capital and labor, across sectors [94]. China's resource-based cities have long relied on resource extraction, with factors flowing toward high-return but energy-intensive sectors rather than emerging technology industries. This leads to widespread inefficiencies in resource allocation [95]. Resource misallocation represents a key bottleneck limiting improvements in CEE. This associational mechanism reflects a key constraint in the low-carbon transition of resource-based cities.

As shown in Table 6, the coefficient on DIT is negative and statistically significant, implying that higher levels of DIT are associated with lower resource misallocation. DIT achieves this by enabling intelligent decision-making, improving supply–demand alignment, and lowering information barriers. Reducing resource misallocation shifts production resources from low-efficiency, high-energy-use sectors to eco-friendly, high-efficiency industries. This shift lowers energy consumption and, in turn, enhances CEE. These findings provide empirical evidence consistent with Hypothesis 2, indicating that reductions in resource misallocation constitute an important associational channel linking DIT and CEE in resource-based cities.

Importantly, this channel reflects a structural efficiency effect of DIT. By correcting existing distortions rather than relying on technological breakthroughs, the reduction in resource misallocation can generate relatively rapid and broad-based improvements in CEE. From a policy perspective, this finding underscores the importance of using DIT as a governance tool to improve market coordination—such as through digital platforms for factor markets, smart regulation, and data-sharing mechanisms—especially in cities where legacy industrial structures remain dominant.

Table 6. Mechanism results: resource misallocation.

Variables	(1) <i>Rm</i>	(2) <i>Rm</i>
<i>Dit</i>	−0.293 *** (0.081)	−0.264 *** (0.081)
Controls	No	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	1100	1100
R ²	0.520	0.522

Note: Standard errors in (); *** indicates significance at the 1% level.

5.3.2. Effect of Improving Green Technological Innovation

Green technological innovation encompasses technological advancements that reduce environmental pollution and energy consumption [96]. It is crucial for decreasing dependence on natural resources, mitigating environmental risks in resource-based cities

[97], and supporting the transition from resource-driven to innovation-driven growth. By doing so, it unlocks the long-term potential for improving CEE.

As reported in Table 7, the coefficient on DIT is positive and statistically significant, indicating that DIT promotes green technological innovation. DIT contributes by virtualizing R&D, promoting multi-level collaboration between firms and governments, and integrating cross-boundary knowledge. These mechanisms shorten development cycles and enhance green technological innovation. In turn, green technological innovation drives the development and diffusion of low-carbon and energy-efficient technologies, improving energy efficiency and enhancing CEE. These findings are consistent with Hypothesis 3, suggesting that green technological innovation serves as an important associational pathway through which DIT is linked to improvements in CEE.

While this channel may operate more gradually than resource reallocation, it plays a critical role in sustaining long-term carbon efficiency improvements. Accordingly, the policy implication is that DIT should be complemented by innovation-oriented measures—such as green R&D subsidies, digital platforms for collaborative innovation, and intellectual property protection—to fully unlock its potential in driving green technological progress.

Table 7. Mechanism results: green technological innovation.

Variables	(1) <i>Gti</i>	(2) <i>Gti</i>
<i>Dit</i>	0.615 *** (0.095)	0.617 *** (0.095)
Controls	No	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	1100	1100
R ²	0.929	0.929

Note: Standard errors in (); *** indicates significance at the 1% level.

5.4. Heterogeneity Analysis

5.4.1. Heterogeneity Across Green Finance

Green finance serves as a critical financial channel for directing capital toward environmentally sustainable activities and thus plays a pivotal role in amplifying the efficiency-enhancing effects of DIT in resource-based cities. As a capital-intensive transformation, DIT requires substantial upfront investment in digital infrastructure, intelligent equipment, and data platforms. In cities with well-developed green finance systems, targeted credit and preferential financing alleviate firms' constraints and enable investment in both digital technologies and low-carbon production [77,98]. This complementarity allows DIT to be more effectively translated into improvements in CEE. By contrast, in cities with underdeveloped green finance, limited access to long-term and low-cost green capital constrains firms' ability to undertake large-scale and integrated DIT projects. Digital investments in such contexts tend to be fragmented or short-term, reducing their capacity to generate sustained improvements in energy efficiency and emissions performance. To examine this heterogeneity, green finance is measured as the share of environmental-project loans in total credit. The sample is categorized into high- and low-green-finance subgroups based on the annual median across resource-based cities. Regressions are then estimated separately for each subgroup.

As shown in Table 8, DIT has a substantial positive effect on CEE in cities with stronger green finance, whereas the effect is statistically insignificant in cities with weaker green finance. The coefficient difference between the two subgroups is significant at the

1% level, confirming pronounced heterogeneity. This divergence reflects a financing-constraint mechanism. In high green-finance cities, ample capital supports investment in integrated DIT-low-carbon solutions—such as AI-optimized energy management systems and smart grid infrastructure—thereby generating synergies between digitalization and emission reduction. In contrast, credit-constrained cities face binding investment trade-offs, whereby limited funds must be allocated between basic digital infrastructure and emission-reduction technologies, weakening the effectiveness of both. Overall, these findings underscore that green finance functions as a key enabling condition for DIT to realize its carbon-efficiency potential, suggesting that strengthening green financial systems is essential for maximizing the low-carbon returns to digital investment.

Table 8. Results of heterogeneity across green finance.

Variables	Low	High
	(1) <i>Cee</i>	(2) <i>Cee</i>
<i>Dit</i>	0.040 (0.259)	0.437 ** (0.197)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	528	535
R ²	0.709	0.766
Chow test	0.544 ***	

Note: Standard errors in (); *** and ** indicate significance at the 1% and 5% levels, respectively.

5.4.2. Heterogeneity Across Digital Infrastructure

Digital infrastructure constitutes the physical and technological foundation for implementing DIT in resource-based cities [99]. The effectiveness of DIT depends on the availability and quality of digital infrastructure—such as broadband networks and data centers—which determine whether digital technologies can be fully embedded in production and energy management. In cities with advanced digital infrastructure, DIT facilitates real-time data collection, cross-sector information sharing, and intelligent optimization of energy use and emissions control, thereby enhancing marginal efficiency gains from digital intelligence adoption. By contrast, in cities with weaker infrastructure, limited network coverage and inadequate digital facilities constrain firms' ability to absorb and utilize advanced digital technologies, resulting in diminished returns to DIT investment. To examine this heterogeneity, digital infrastructure is proxied by the internet penetration rate. The sample is divided into high- and low-infrastructure subgroups based on the annual median, and regressions are estimated for each subset. The results are presented in Table 9.

Table 9. Results of heterogeneity across digital infrastructure.

Variables	Low	High
	(1) <i>Cee</i>	(2) <i>Cee</i>
<i>Dit</i>	−0.018 (0.268)	0.360 * (0.197)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	536	550
R ²	0.711	0.749
Chow test	0.841 ***	

Note: Standard errors in (); *** and * indicate significance at the 1% and 10% levels, respectively.

The findings show that DIT significantly improves CEE in cities with advanced digital infrastructure, while its effect is not statistically significant in areas with less-developed infrastructure. The coefficient difference test, significant at the 1% level, confirms the presence of heterogeneous effects. This heterogeneity is consistent with infrastructure-technology complementarity theory. In high-infrastructure cities, governments and firms can deploy integrated digital intelligence platforms that consolidate energy, emissions, and production data in real time, enabling system-wide optimization of carbon performance. For instance, smart manufacturing systems can dynamically adjust production parameters in response to energy price signals and emission constraints. In contrast, in low-infrastructure cities, fragmented digital capabilities hinder such integration: incomplete data collection, transmission delays, and insufficient computational capacity prevent advanced analytics and real-time optimization. Consequently, DIT is often confined to isolated or partial applications rather than generating transformative efficiency gains. These findings suggest that investment in digital infrastructure should precede or accompany DIT initiatives, particularly in lagging regions, to ensure that digital intelligence can effectively translate into carbon efficiency improvements.

5.4.3. Heterogeneity Across Types of Resource-Based Cities

The National Plan for Sustainable Development of Resource-Based Cities (2013–2020) classifies resource-based cities into four types: growing, mature, declining, and regenerative. Differences in resource stability and sustainable development capacity across these types suggest that the effects of DIT on CEE may be heterogeneous [97]. To explore this, the sample is divided by city type, and separate regressions are conducted for each subgroup.

As shown in Table 10, DIT does not have a statistically significant effect on CEE in growing resource-based cities. These cities are still expanding their resource extraction capacity, and DIT investments are primarily directed toward managing incremental production rather than optimizing existing energy-intensive processes. Consequently, the scope for efficiency gains through DIT remains limited at this stage. In contrast, DIT significantly improves CEE in mature and regenerative cities. These cities typically possess more complete industrial systems and stronger institutional capacity, which allows DIT to be integrated into industrial upgrading, energy substitution, and emissions management. In such contexts, digital intelligence technologies complement ongoing structural transformation, enabling firms to reduce energy intensity and improve carbon efficiency.

Table 10. Results of heterogeneity across types of resource-based cities.

Variables	Growing	Mature	Declining	Regenerative
	(1) <i>Cee</i>	(2) <i>Cee</i>	(3) <i>Cee</i>	(4) <i>Cee</i>
<i>Dit</i>	−0.173 (0.252)	0.611 *** (0.233)	−2.304 *** (0.549)	0.757 *** (0.141)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	140	580	230	150
R ²	0.766	0.767	0.779	0.795
Chow test	−1.029 **		−1.561 ***	

Note: Standard errors in (); *** and ** indicate significance at the 1% and 5% levels, respectively.

Notably, DIT is found to exert a negative effect on CEE in declining resource-based cities. This result suggests that the carbon-efficiency implications of digital intelligence transformation are highly context-dependent and may differ substantially across stages of resource development. Several factors may help rationalize this finding. Declining cities

often exhibit strong resource lock-in and outdated industrial structures, limiting the potential for digital technologies to support green transformation. In such settings, early-stage DIT investments may be used primarily to sustain existing production systems rather than to facilitate energy substitution or capacity reduction. In addition, transitional adjustment costs may arise if scarce fiscal and financial resources are reallocated toward digital projects at the expense of environmental remediation or clean-energy investment. Moreover, weak absorptive capacity—stemming from shortages of skilled labor, managerial expertise, and complementary institutions—may further constrain the efficiency gains from DIT, leading to short-term deterioration in carbon emission efficiency.

Chow tests further indicate that coefficient differences between growing and mature cities, as well as between declining and regenerative cities, are statistically significant, confirming the robustness of these heterogeneous effects. Overall, these findings suggest that the carbon efficiency impacts of DIT are highly context-dependent. For declining resource-based cities in particular, priority should be given to resolving structural rigidities and phasing out obsolete capacity before scaling up DIT, in order to avoid transitional inefficiencies and unlock its long-term low-carbon potential.

To further examine whether the observed heterogeneity—particularly the pronounced negative coefficient for declining cities—is driven by differential underlying time dynamics rather than the effect of digital intelligence transformation itself, we conduct an additional robustness check by allowing for city-type-specific linear time trends. Specifically, we interact city-type indicators with a linear time trend to capture systematic differences in temporal dynamics across city types. The results, reported in Appendix Table A3, show that after accounting for such differential trends, the estimated coefficient on DIT in the full sample remains positive and statistically significant. This finding indicates that the baseline effect of DIT on carbon emission efficiency is not driven by pre-existing divergent time paths across different types of resource-based cities. Importantly, this exercise does not negate the heterogeneous effects documented in Table 10, but rather suggests that the pronounced negative coefficient observed for declining cities reflects structural and transitional characteristics specific to that group, rather than spurious trend differences.

6. Conclusions and Policy Recommendations

6.1. Conclusions

Using panel data from 110 Chinese resource-based cities from 2013 to 2022, this study measures DIT using the entropy weight method and CEE using the SBM-GML framework. It then examines the impact of DIT on CEE performance. First, DIT significantly enhances CEE in resource-based cities. This positive effect remains robust across multiple robustness checks. Second, associational mechanism analysis indicates that higher levels of DIT are systematically associated with lower resource misallocation and stronger green technological innovation, both of which are in turn linked to higher CEE in resource-based cities. Third, heterogeneity tests indicate that the effect of DIT on CEE is stronger in cities with well-developed green finance, robust digital infrastructure, and at mature or regenerative stages of development.

6.2. Policy Recommendations

To maximize DIT's beneficial impact on CEE in resource-based cities and leverage this impact in advancing SDG 13, three policy recommendations are proposed.

First, DIT should be positioned as a core driver of deep decarbonization in resource-based cities. Policymakers should develop strategies that leverage DIT to enhance efficiency, with a focus on systematically applying digital intelligence in high-carbon sectors

such as coal, metallurgy, and chemicals. Complementary measures, including tax incentives, pilot demonstration projects, and targeted financial subsidies, should be implemented to reduce barriers to technology adoption and accelerate the large-scale deployment of digital intelligence in efficiency-enhancing initiatives. Moreover, collaboration among public agencies, universities, research institutions, industry stakeholders, and civil society is essential to cultivate practical digital intelligence talent. Such talent can help resource-based cities address environmental challenges and more effectively integrate DIT into their sustainable development strategies.

Second, resource misallocation and green technological innovation are the key associational channels through which DIT influences CEE in resource-based cities. Ensuring the smooth functioning of these mechanisms is therefore essential for achieving targeted efficiency improvements. Local governments should take the lead in establishing a digital intelligence platform for factor allocation, coordinated across multiple stakeholders. This platform should identify areas of resource misallocation and recycling potential, facilitate resource reuse, and prioritize directing factors toward low-energy, green industries, thereby promoting efficiency gains.

At the same time, a digital platform for green technologies should be developed to guide R&D through a data-driven “challenge and reward” system. The platform can link innovation outcomes to efficiency improvements through “green patents–carbon benefits” incentives. It can also use data analytics to develop tailored green technology strategies that address the specific emission reduction and efficiency needs of each city.

Third, given the substantial heterogeneity in DIT’s efficiency-enhancing effects across resource-based cities, policy interventions should be tailored to the specific local context, including green finance, digital infrastructure, and development stage. In cities with underdeveloped green finance systems, governments can deploy risk-sharing instruments—such as green credit guarantee schemes, public–private co-investment funds, and transparent project evaluation platforms—to reduce financing barriers for DIT-enabled emission reduction projects. Cities with advanced green finance can leverage their capacity to develop market-oriented “green finance-DIT efficiency gains” ecosystems, fostering long-term sustainable growth. Regarding digital infrastructure, cities with weaker networks should prioritize expanding digital connectivity and computational capacity to support DIT deployment. Cities with advanced infrastructure should implement next-generation digital intelligence applications across diverse emission scenarios, including smart grids, intelligent manufacturing, and real-time emissions monitoring systems. Finally, policies should reflect the city’s development stage. Growing cities should integrate DIT into the management of new projects to prevent carbon lock-in. Mature cities should embed DIT in production optimization and energy management. Declining cities must first address legacy inefficiencies before systematically applying DIT. Regenerative cities should fully implement DIT to establish low-carbon, efficiency-enhancing models that serve as benchmarks for broader sustainable transformation.

Although this study is situated in the Chinese context, its policy implications extend to other resource-dependent regions worldwide. Many resource-based cities in developing and transition economies face similar challenges, including industrial lock-in, financing constraints, and uneven digital infrastructure. Emphasizing mechanism-oriented policy design, differentiated governance tools, and the complementarity between digital intelligence, finance, and structural reform can therefore inform low-carbon transition strategies beyond China, particularly for regions seeking to reconcile economic restructuring with climate mitigation objectives.

6.3. Limitations and Discussion

Although this study offers valuable insights into the effect of DIT on CEE in resource-based cities, several limitations remain, highlighting areas for future research.

First, this study relies on panel data from Chinese resource-based cities covering 2013–2022, which may limit the ability to capture long-term dynamics. Future research could extend the time horizon to better capture the long-term dynamics of DIT's effects on CEE. Incorporating firm-level microdata would also help to deepen understanding of carbon reduction mechanisms at the level of individual decision-making. In addition, due to substantial cross-country differences in environmental conditions and development stages, the findings are primarily applicable to the Chinese context. Cross-country studies could examine whether DIT's efficiency-enhancing effects generalize to other countries and explore country-specific heterogeneity.

Second, while city-level data reflect macro trends, they may obscure industry-specific variations in DIT's impact on efficiency. Future studies should focus on high-emission sectors, including energy, transportation, and manufacturing, to uncover heterogeneous pathways through which DIT influences efficiency at the sectoral level. Understanding the distinct challenges and opportunities within each industry during decarbonization transitions would provide a strong empirical foundation for targeted, industry-specific sustainability strategies.

Third, although this study examines resource misallocation and green technological innovation as primary channels, other mechanisms such as the green transformation of household consumption warrant further investigation. In addition, this research does not fully account for the dynamic moderating effects of external institutional factors, such as environmental policy stringency. Future research could incorporate a broader set of external variables, including regulatory intensity and public participation in environmental governance, to improve model explanatory power. This would provide a more comprehensive understanding of sustainable development and generate broader insights for promoting high-quality economic growth.

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Appendix A. Calculation Procedure of CEE

Building on the analytical approach developed by Ding et al. (2025), CEE is quantified using the SBM–GML method. The calculation proceeds in three steps [1]:

Appendix A.1. The Slacks-Based Measure (SBM) Analytical Framework

Drawing on the formulation proposed by Tone (2001), the slacks-based measure (SBM) model that accounts for undesirable outputs is defined as follows [79]:

$$\rho^* = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_i}}{1 + \frac{1}{s^+ q} \left(\sum_{r=1}^s \frac{s_r^+}{y_r^g} + \sum_{h=1}^q \frac{s_h^b}{y_h^b} \right)} \quad (A1)$$

with the constraints of

$$x = X\lambda + s^-, y^g = Y^g\lambda - s^+, y^b = Y^b\lambda + s^b, \lambda \geq 0, s^-, s^+, s^b \geq 0 \quad (A2)$$

where x denotes inputs, y^g desirable outputs, y^b undesirable outputs, s^- , s^+ , and s^b are slack variables, and λ is the intensity vector. An efficiency score of $\rho^*=1$ indicates full efficiency.

Appendix A.2. The GML Index

Drawing on the framework of Oh (2010), the global Malmquist–Luenberger (GML) metric across period t and $t + 1$ is defined as follows [82]:

$$GML^{t \rightarrow t+1}(x_t, y_t^g, y_t^b, x_{t+1}, y_{t+1}^g, y_{t+1}^b) = \frac{1 + D^G(x_{t+1}, y_{t+1}^g, y_{t+1}^b)}{1 + D^G(x_t, y_t^g, y_t^b)} \quad (A3)$$

where $D^G(\cdot)$ refers to the directional distance function corresponding to the global technology portfolio.

Appendix A.3. Calculation of CEE

As the GML index captures productivity changes between consecutive periods, CEE is computed as the cumulative multiplication of sequential GML index figures, with 2011 set as the base year:

$$Cee_{it} = \prod_{\tau=2011}^{t-1} GML_i^{\tau \rightarrow \tau+1} \quad (A4)$$

Appendix B. Third-Level Indicators of DIT

Digitalization serves as the “data foundation” of DIT and is treated as a first-level indicator. Following the classification framework of Liu and Lin (2025), it is further subdivided into seven third-level indicators, measured as follows [100]:

- (1) Internet users per 100 people (*Dig1*): Computed as the proportion of broadband Internet registered users to the permanent resident population.
- (2) Mobile-phone users per 100 people (*Dig2*): Calculated as the ratio of year-end mobile-phone service holders to the city’s permanent resident population.
- (3) Peking University Digital Inclusive Finance Index (*Dig3*): Data are retrieved from the Digital Financial Inclusion Index compiled by the Peking University Digital Finance Research Center and Ant Group.
- (4) Telecom revenue per capita (*Dig4*): Computed as total telecom revenue split by the city’s permanent resident population size.
- (5) E-commerce transaction volume (*Dig5*): Measured as the gross merchandise value (GMV) on trading platforms, including both paid and confirmed but unpaid orders. Since city-level data are unavailable, each city’s transaction volume is estimated by multiplying national GMV by the city’s share of the national express-delivery business.
- (6) Number of digital technology patent applications (*Dig6*): Core digital technology industries, as defined in the Zhejiang Digital Economy Statistical Classification, are mapped to IPC codes using the 2018 mapping table published by China’s National Bureau of Statistics. City-level patent filings are then retrieved from the Dawei Patent Database.

- (7) Share of computer services and software employees (*Dig7*): Determined as employment in computer services and software as a percentage of the overall urban-unit employees.

Intelligence, serving as the “intelligent core” of DIT, is treated as a first-level indicator. Following Xia et al. (2024), it is further disaggregated into three third-level indicators, with the following measurement methods [101]:

- (1) Number of AI enterprises (*Int1*): Business-scope texts from Tianyancha’s corporate registry are analyzed to identify firms containing predefined AI-related keywords; city-level counts are aggregated by registered address.
- (2) Robot installation density (*Int2*): Industrial-robot installation data by sector are obtained from the IFR. Sectoral employment at the city level is derived from China’s 2008 Economic Census. Robot densities are calculated at the city-sector level, weighted by employment shares, and aggregated to produce city-level installation density.
- (3) Number of AI patent applications (*Int3*): City-level AI patent datasets are retrieved from the database of the China National Intellectual Property Administration (CNIPA), alongside the Derwent Innovations platform. AI-related patents are identified using a combination of relevant IPC codes and AI-specific keywords in the patent title and abstract.

To examine the contribution of individual indicators, we compute the correlation coefficients between each third-level indicator and the overall DIT index. This analysis also helps assess potential concerns regarding weight dominance in the composite index. As reported in Table A1, all indicators are positively correlated with the composite index. Importantly, the correlation magnitudes are relatively balanced, with no single indicator exhibiting an excessively strong association with the overall DIT measure. This evidence suggests that the constructed DIT index captures a broad-based process of digital intelligence transformation rather than being mechanically driven by any single indicator or dimension.

Table A1. Correlations between individual indicators and the composite DIT index.

Indicators	(1) <i>Dig1</i>	(2) <i>Dig2</i>	(3) <i>Dig3</i>	(4) <i>Dig4</i>	(5) <i>Dig5</i>	(6) <i>Dig6</i>	(7) <i>Dig7</i>	(8) <i>Int1</i>	(9) <i>Int2</i>	(10) <i>Int3</i>
Correlation with DIT	0.506	0.503	0.569	0.520	0.746	0.765	0.487	0.734	0.419	0.697

Appendix C. Calculation Procedure of DIT

The level of DIT is assessed via the entropy weight approach, which allocates weights to metrics according to their information content, thus reflecting the respective contribution of individual metrics. Metrics with greater entropy—indicating lower information content—are given smaller weights, whereas those with lower entropy obtain larger weights. This computation is carried out in three phases:

Appendix C.1. Data Standardization

For each indicator x_{ij} , data are normalized as follows:

For positively directional metrics:

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (\text{A5})$$

For negatively directional metrics:

$$z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (\text{A6})$$

where z_{ij} denotes the standardized value.

Appendix C.2. Entropy Value of Each Indicator

The share of city i corresponding to indicator j is defined as

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^n z_{ij}} \quad (\text{A7})$$

The information entropy associated with indicator j is subsequently computed as

$$e_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}), \quad k = \frac{1}{\ln(n)} \quad (\text{A8})$$

where n represents the total count of cities.

Appendix C.3. Indicator Weights and Composite Index

The redundancy (information utility) of indicator j is

$$d_j = 1 - e_j \quad (\text{A9})$$

The weight of indicator j is

$$\omega_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (\text{A10})$$

Finally, for city i , its DIT score is computed as

$$Dit_i = \sum_{j=1}^m \omega_j \times z_{ij} \quad (\text{A11})$$

where m represents the overall quantity of indicators.

Appendix D. Computation Procedure for Resource Misallocation

Building upon the analytical framework proposed by Hsieh and Klenow (2009), resource misallocation is measured by jointly capturing capital and labor misallocation. The calculation proceeds in three steps [86]:

Appendix D.1. Cobb–Douglas Production Function

We assume a Cobb–Douglas (C-D) production function and take its logarithm, yielding

$$\ln Y_{it} = \ln A + \alpha \ln k_{it} + \beta \ln L_{it} \quad (\text{A12})$$

where Y_{it} denotes gross output, proxied by real GDP; A represents technological progress; k_{it} represents capital input, assessed using the capital stock derived through the perpetual inventory approach (with 2011 set as the benchmark year); while L_{it} denotes labor input, gauged by year-end employment figures. α and β are the output elasticities corresponding to capital and labor (in that order), estimated via regression on the C-D production function. The marginal products of capital and labor are derived by computing the partial derivatives of Y_{it} with regard to k_{it} and L_{it} —this yields $\alpha Y_{it}/K_{it}$ and $\beta Y_{it}/L_{it}$, in sequence.

Appendix D.2. Capital and Labor Misallocation

Let the price of capital be r_{it} while the labor input's price be w_{it} . The extent pertaining to capital and labor misallocation is measured by the divergence between their marginal products from their respective prices:

$$distK_{it} = |\alpha Y_{it}/r_{it}K_{it} - 1| \quad (A13)$$

$$distL_{it} = |\beta Y_{it}/w_{it}L_{it} - 1| \quad (A14)$$

where $distK_{it}$ represents capital misallocation and $distL_{it}$ denotes labor misallocation. Larger absolute values indicate more severe misallocation. Here, r_{it} is set at 10% (5% depreciation plus 5% real interest rate, and w_{it} is represented by the mean wage per employee. Other variables are consistent with Equation (A12).

Appendix D.3. Computation of Resource Misallocation

Integrate capital and labor misallocation, and then obtain the overall degree of market distortion.

$$dist_{it} = distK_{it}^{\frac{\alpha}{\alpha+\beta}} distL_{it}^{\frac{\beta}{\alpha+\beta}} \quad (A15)$$

where $dist_{it}$ represents degree of market distortion. Finally, each city's degree of resource misallocation (Rm) is calculated as the ratio of its $dist_{it}$ relative to the highest $dist_{it}$ value across all resource-dependent cities in the identical year.

Appendix E. Spatial Robustness Check

To further account for potential spatial interactions across cities, we estimate a Spatial Durbin Model (SDM), which allows for both endogenous interaction effects and exogenous spillovers from neighboring cities. The spatial weight matrix is specified as an inverse geographic distance matrix, capturing proximity-based interactions while avoiding arbitrary contiguity assumptions. Table A2 reports the estimation results. The estimated coefficient and long-run direct effect of DIT remain positive and statistically significant after accounting for spatial dependence, confirming the robustness of the baseline findings. By contrast, neither the spatially lagged DIT term nor the long-run indirect effect is statistically significant. This result suggests limited inter-city spillovers of digital intelligence transformation during the sample period.

The absence of significant spatial spillovers may be attributed to two structural characteristics of China's resource-based city system. First, resource-based cities are geographically dispersed rather than spatially clustered at the national level. Second, many of these cities are located far from major innovation hubs and high-density economic centers, and their industrial systems are relatively self-contained. These features constrain knowledge diffusion and economic interactions based on geographic proximity, thereby weakening the scope for geographically mediated spillover effects.

Table A2. Regression results of the spatial econometric model.

Variables	Cee
<i>Dit</i>	0.388 *** (0.116)
<i>WDit</i>	−0.467 (1.127)
LR_Direct <i>Dit</i>	0.400 *** (0.121)

LR_Indirect <i>Dit</i>	−0.440 (0.676)
Controls	Yes
City FE	Yes
Year FE	Yes
sigma2_e	0.012 *** (0.001)
Observations	1100
R ²	0.024

Note: Standard errors in (); *** indicates significance at the 1% level.

Appendix F. Robustness Check with City-Type-Specific Linear Time Trends

To assess whether heterogeneous effects across different types of resource-based cities—particularly the negative coefficient for declining cities—are driven by underlying time dynamics rather than digital intelligence transformation itself, we conduct an additional robustness check. Specifically, we allow for city-type-specific linear time trends. Specifically, we interact city-type indicators (growing, mature, declining, and regenerative) with a common linear time trend, thereby flexibly capturing systematic differences in temporal evolution across city types. Table A3 reports the estimation results. After accounting for city-type-specific time trends, the coefficient on DIT in the full sample remains positive and statistically significant. This result suggests that the baseline relationship between digital intelligence transformation and carbon emission efficiency is robust to heterogeneous time dynamics across city types and is not driven by unmodeled pre-existing trends.

Table A3. Robustness check results with city-type-specific time.

Variables	<i>Cee</i>
<i>Dit</i>	0.367 ** (0.144)
Controls	Yes
City FE	Yes
Year FE	Yes
City-type × Time Trend	Yes
Observations	1100
R ²	0.752

Note: Standard errors in (); ** indicates significance at the 5% level.

References

1. Ding, S.; Wei, S.; Zhang, H.; Hu, J. Promotion or inhibition? Unveiling the heterogeneous effects and mechanism of the digital economy on carbon emission efficiency. *Energy Econ.* **2025**, *149*, 108803. <https://doi.org/10.1016/j.eneco.2025.108803>.
2. Lee, C.C.; Fang, Y.; Quan, S.; Li, X. Leveraging the power of artificial intelligence toward the energy transition: The key role of the digital economy. *Energy Econ.* **2024**, *135*, 107654. <https://doi.org/10.1016/j.eneco.2024.107654>.
3. Cheba, K.; Bąk, I.; Szopik-Depczyńska, K. Sustainable competitiveness as a new economic category—Definition and measurement assessment. *Technol. Econ. Dev. Econ.* **2020**, *26*, 1399–1421. <https://doi.org/10.3846/tede.2020.13528>.
4. Lee, C.C.; He, Z.W.; Yuan, Z. A pathway to sustainable development: Digitization and green productivity. *Energy Econ.* **2023**, *124*, 106772. <https://doi.org/10.1016/j.eneco.2023.106772>.
5. Wang, M.; Feng, C. The win-win ability of environmental protection and economic development during China's transition. *Technol. Forecast. Soc. Chang.* **2021**, *166*, 120617. <https://doi.org/10.1016/j.techfore.2021.120617>.

6. Xing, M.; Liu, X.; Luo, F. How does the development of urban agglomeration affect the electricity efficiency of resource-based cities?—An empirical research based on the fsQCA method. *Socio-Econ. Plan. Sci.* **2023**, *86*, 101479. <https://doi.org/10.1016/j.seps.2022.101479>.
7. Li, J.; Yang, H.; Zhong, S.; Zhong, Y. Exploring the Effect of Integration Development of Digital Intelligence on Green Technology Innovation Quantity and Quality. *Sustainability* **2025**, *17*, 4339. <https://doi.org/10.3390/su17104339>.
8. Chen, J.; Zhang, Y.; Wang, M. Digital intelligence technology innovation, energy transformation and urban carbon emission efficiency. *Chin. J. Popul. Resour. Environ.* **2025**, *23*, 205–219. <https://doi.org/10.1016/j.cjpre.2025.05.006>.
9. Hao, M.; Zhang, F.; Xu, S.; Dong, Z.; He, Z. The impact of digital intelligence on energy-intensive firms' green transformation. *Environ. Res. Commun.* **2025**, *7*, 025016. <https://doi.org/10.1088/2515-7620/adaa56>.
10. Cao, B.; Li, L.; Zhang, K.; Ma, W. The influence of digital intelligence transformation on carbon emission reduction in manufacturing firms. *J. Environ. Manag.* **2024**, *367*, 121987. <https://doi.org/10.1016/j.jenvman.2024.121987>.
11. Wang, Z.; Jia, H.; Wu, J. The Impact of Urban Digital Intelligence Transformation on Corporate Carbon Performance: Evidence from China. *Sustainability* **2025**, *17*, 5591. <https://doi.org/10.3390/su17125591>.
12. Tan, X.; Jiao, J.; Jiang, M.; Chen, M.; Wang, W.; Sun, Y. Digital policy, green innovation, and digital-intelligent transformation of companies. *Sustainability* **2024**, *16*, 6760. <https://doi.org/10.3390/su16166760>.
13. Guo, X.; Xu, J. Carbon reduction in the AI era: How does urban digital intelligence transformation facilitate low-carbon development? *Urban Clim.* **2025**, *61*, 102449. <https://doi.org/10.1016/j.uclim.2025.102449>.
14. Lobonț, O.-R.; Criste, C.; Bovary, C.; Țăran, A.-M. Settling the debate: Does digitalisation impact the economic growth in the European Union Member States? *Technol. Econ. Dev. Econ.* **2025**, *31*, 980–1007. <https://doi.org/10.3846/tede.2025.22576>.
15. Neffati, M.; Jbir, R. The impact of digitalization and economic diversification on economic growth: Evidence from Saudi Arabia. *Technol. Econ. Dev. Econ.* **2024**, *30*, 1510–1532. <https://doi.org/10.3846/tede.2024.22105>.
16. Zlati, M.L.; Fortea, C.; Antohi, V.-M.; Cristache, N.; Dinca, M.S.; Balsalobre-Lorente, D. Refreshing the design of a regional economic growth model in the context of the new digital decade. *Technol. Econ. Dev. Econ.* **2025**, *1*–38. <https://doi.org/10.3846/tede.2025.24534>.
17. Gao, C.; Fang, J. The Green Effect of Digital Intelligence in Chinese Cities: An Empirical Investigation Based on Big Data and Machine Learning Methods. *Sustainability* **2025**, *17*, 6728. <https://doi.org/10.3390/su17156728>.
18. Yuan, C.; Liu, J.; Fan, Y. Exploring the dynamics of urban digital intelligent transformation: Sustainable development through the National AI innovation pilot zone. *Environ. Dev. Sustain.* **2025**, *1*–36. <https://doi.org/10.1007/s10668-025-06526-4>.
19. Sun, Q.; Liu, S.; Feng, L.; Lu, G. Nonlinear relationship between digital and intelligent transformation and energy conservation and emission reduction in China. *Sci. Rep.* **2025**, *15*, 29814. <https://doi.org/10.1038/s41598-025-15821-z>.
20. Li, J.; Han, X.; Zhang, T.; Xiao, J.; Chen, L. Digital intelligence and synergy of pollution reduction and carbon reduction: “Dividend” or “gap”? *Chin. J. Popul. Resour. Environ.* **2024**, *22*, 389–398. <https://doi.org/10.1016/j.cjpre.2024.11.003>.
21. Zhao, R.; Sun, J.; Wu, J. Does the integration of finance and technology bring policy dividends for low-carbon development? Quasi-experimental evidence from China. *Chin. J. Popul. Resour. Environ.* **2025**, *23*, 470–479. <https://doi.org/10.1016/j.cjpre.2025.10.005>.
22. Zhang, N.; Wang, B.; Liu, Z. Carbon emissions dynamics, efficiency gains, and technological innovation in China's industrial sectors. *Energy* **2016**, *99*, 10–19. <https://doi.org/10.1016/j.energy.2016.01.012>.
23. Xie, Z.; Wu, R.; Wang, S. How technological progress affects the carbon emission efficiency? Evidence from national panel quantile regression. *J. Clean. Prod.* **2021**, *307*, 127133. <https://doi.org/10.1016/j.jclepro.2021.127133>.
24. Zhao, S.; Zhang, X. Did digitalization of manufacturing industry improved the carbon emission efficiency of exports: Evidence from China. *Energy Strategy Rev.* **2025**, *57*, 101614. <https://doi.org/10.1016/j.esr.2024.101614>.
25. Qu, S.; Xu, Y.; Ji, Y.; Feng, C.; Wei, J.; Jiang, S. Data-driven robust data envelopment analysis for evaluating the carbon emissions efficiency of provinces in China. *Sustainability* **2022**, *14*, 13318. <https://doi.org/10.3390/su142013318>.
26. Zeng, P.; Tang, H.; Wei, X. Quantitative simulation and validation of energy carbon emission efficiency changes in Chinese urban agglomerations. *Energy* **2024**, *312*, 133442. <https://doi.org/10.1016/j.energy.2024.133442>.
27. Hu, J.; Shi, H.; Huang, Q.; Luo, Y.; Li, Y. The impacts of freight trade on carbon emission efficiency: Evidence from the countries along the “Belt and Road”. *Complexity* **2020**, 2529718. <https://doi.org/10.1155/2020/2529718>.
28. Wang, Z.; Shao, H. Spatiotemporal interactions and influencing factors for carbon emission efficiency of cities in the Yangtze River Economic Belt, China. *Sustain. Cities Soc.* **2024**, *103*, 105248. <https://doi.org/10.1016/j.scs.2024.105248>.

29. Liu, J.; Zhang, P.; Wang, X. Exploring the Mechanisms and Pathways Through Which the Digital Transformation of Manufacturing Enterprises Enhances Green and Low-Carbon Performance Under the “Dual Carbon” Goals. *Sustainability* **2025**, *17*, 1162. <https://doi.org/10.3390/su17031162>.
30. Shi, P.; Huang, Q. Assessing the evolution and convergence of energy-related carbon emission efficiency in the Yangtze River Economic Belt. *Process Saf. Environ. Prot.* **2024**, *191*, 1684–1695. <https://doi.org/10.1016/j.psep.2024.09.058>.
31. Pan, Y.; Weng, G.; Li, C.; Li, J. Coupling coordination and influencing factors among tourism carbon emission, tourism economic and tourism innovation. *Int. J. Environ. Res. Public Health* **2021**, *18*, 1601. <https://doi.org/10.3390/ijerph18041601>.
32. Wang, Z.; Xu, X.; Zhu, Y.; Gan, T. Evaluation of carbon emission efficiency in China’s airlines. *J. Clean. Prod.* **2020**, *243*, 118500. <https://doi.org/10.1016/j.jclepro.2019.118500>.
33. Liao, T.; Yan, J.; Zhang, Q. The impact of green technology innovation on carbon emission efficiency: The intermediary role of intellectual capital. *Int. Rev. Econ. Financ.* **2024**, *92*, 520–532. <https://doi.org/10.1016/j.iref.2024.02.016>.
34. Wen, Z.; Lee, W.S.; Woo, S. Impact of land resource misallocation on carbon emission efficiency: Empirical evidence from 274 cities in China. *Front. Environ. Sci.* **2025**, *13*, 1652558. <https://doi.org/10.3389/fenvs.2025.1652558>.
35. Cao, Y.; Ji, X.; Yao, J.; Xu, N.; Chen, M.; Yang, X.; Liu, Z.; Li, Z.; Mo, F. Research on coupling coordination of agricultural carbon emission efficiency and food security in Hebei province, China. *Sustainability* **2024**, *16*, 5306. <https://doi.org/10.3390/su16135306>.
36. Nie, L.; Bao, X.; Song, S.; Wu, Z. The impact of the digital economy on total-factor carbon emission efficiency in the yellow river basin from the perspectives of mediating and moderating roles. *Systems* **2024**, *12*, 99. <https://doi.org/10.3390/systems12030099>.
37. Hu, H.; Zhang, W. Influencing factors and realistic path of digital and intelligent transformation in manufacturing enterprises: A dynamic QCA analysis based on the TOE framework. *Technol. Anal. Strateg. Manag.* **2025**, 1–16. <https://doi.org/10.1080/09537325.2025.2503424>.
38. Xue, S.; Chen, S. The acceptance of digital intelligence technology in megaproject organisations from the perspective of innovation diffusion. *Technol. Anal. Strateg. Manag.* **2024**, *38*, 65–80. <https://doi.org/10.1080/09537325.2024.2372804>.
39. Liu, Y.; Song, P. Research on the influence of firm digital intelligence transformation and management innovation on performance and sustainable development: Empirical evidence from China. *Sustainability* **2024**, *16*, 7578. <https://doi.org/10.3390/su16177578>.
40. Chen, J.; Sun, H.; Han, R.; Cai, Z. The emerging driving force of inclusive green growth in Chinese cities: The role of digital intelligence. *Appl. Econ.* **2025**, 1–18. <https://doi.org/10.1080/00036846.2025.2523020>.
41. Guo, X.; Xu, J. Can urban digital intelligence transformation promote corporate green innovation? Evidence from China. *J. Environ. Manag.* **2024**, *371*, 123245. <https://doi.org/10.1016/j.jenvman.2024.123245>.
42. Zhao, J.; Wang, X.; Yao, X.; Xi, X. Digital-intelligence transformation, for better or worse? The roles of pace, scope and rhythm. *Internet Res.* **2024**, *35*, 1465–1507. <https://doi.org/10.1108/intr-12-2023-1125>.
43. Zhang, Z.; Li, P.; Huang, L.; Kang, Y. The impact of artificial intelligence on green transformation of manufacturing enterprises: Evidence from China. *Econ. Change Restruct.* **2024**, *57*, 146. <https://doi.org/10.1007/s10644-024-09730-w>.
44. Pang, Q.; Liu, X.; Su, M. Leveraging Digital Intelligence Technologies for Green Shipping: Organization Information Processing and Contingency Perspective. *Bus. Strategy Environ.* **2025**, *34*, 9023–9039. <https://doi.org/10.1002/bse.70056>.
45. Ding, Q.; He, W.; Deng, Y. Can tax reduction incentive policy promote corporate digital and intelligent transformation? *Int. Rev. Financ. Anal.* **2025**, *99*, 103932. <https://doi.org/10.1016/j.irfa.2025.103932>.
46. Jia, J.; Guan, T.; Han, J.; Wang, K.; Bao, Z.; Xu, R.; Lv, K. Empirical study on high quality transition of energy system with digital intelligence driving green development. *Discov. Sustain.* **2025**, *6*, 603. <https://doi.org/10.1007/s43621-025-01446-9>.
47. Deng, L.; Zhong, Z. The impact of digital infrastructure on carbon emissions: Evidence from 284 cities in China. *Econ. Chang. Restruct.* **2024**, *57*, 159. <https://doi.org/10.1007/s10644-024-09745-3>.
48. Zhao, H.; Guo, S. Analysis of the non-linear impact of digital economy development on energy intensity: Empirical research based on the PSTR model. *Energy* **2023**, *282*, 128867. <https://doi.org/10.1016/j.energy.2023.128867>.
49. Lu, D.; Wang, Z. Towards green economic recovery: How to improve green total factor productivity. *Econ. Chang. Restruct.* **2023**, *56*, 3163–3185. <https://doi.org/10.1007/s10644-023-09515-7>.
50. Guo, Q.; Peng, Y.; Luo, K. The impact of artificial intelligence on energy environmental performance: Empirical evidence from cities in China. *Energy Econ.* **2025**, *141*, 108136. <https://doi.org/10.1016/j.eneco.2024.108136>.
51. Liu, Y.; Guo, J.; Shen, F.; Song, Y. Can artificial intelligence technology improve green total factor efficiency in energy utilisation? Empirical evidence from 282 cities in China. *Econ. Chang. Restruct.* **2025**, *58*, 23. <https://doi.org/10.1007/s10644-025-09862-7>.
52. Selvaraj, R.; Kuthadi, V.M.; Baskar, S. Smart building energy management and monitoring system based on artificial intelligence in smart city. *Sustain. Energy Technol. Assess.* **2023**, *56*, 103090. <https://doi.org/10.1016/j.seta.2023.103090>.

53. Manikandan, S.; Kaviya, R.S.; Shreeharan, D.H.; Subbaiya, R.; Vickram, S.; Karmegam, N.; Kim, W.; Govarthanan, M. Artificial intelligence-driven sustainability: Enhancing carbon capture for sustainable development goals—A review. *Sustain. Dev.* **2025**, *33*, 2004–2029. <https://doi.org/10.1002/sd.3222>.
54. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. <https://doi.org/10.1016/j.jbusres.2020.08.019>.
55. Lapinskaitė, I.; Ingaunytė, N.; Zemlickienė, V.; Martinkutė-Kaulienė, R. Navigating the digital landscape: Situation and risk assessment of digital solutions in forwarding companies. *Technol. Econ. Dev. Econ.* **2024**, *30*, 976–1008. <https://doi.org/10.3846/tede.2024.21366>.
56. Tian, H.; Qin, J.; Cheng, C.; Javeed, S.A.; Chu, T. Towards low-carbon sustainable development under Industry 4.0: The influence of industrial intelligence on China's carbon mitigation. *Sustain. Dev.* **2024**, *32*, 455–480. <https://doi.org/10.1002/sd.2664>.
57. Zhang, G.; Wang, X.; Xie, J.; Hu, Q. A mechanistic study of enterprise digital intelligence transformation, innovation resilience, and firm performance. *Systems* **2024**, *12*, 186. <https://doi.org/10.3390/systems12060186>.
58. Gorwa, R. What is platform governance? *Inf. Commun. Soc.* **2019**, *22*, 854–871. <https://doi.org/10.1080/1369118x.2019.1573914>.
59. Liang, Y.; Zhou, C.; Wu, Y. The emerging driving force of green transformation in resource-based cities: Does the digital economy work? *Econ. Anal. Policy* **2025**, *86*, 1858–1880. <https://doi.org/10.1016/j.eap.2025.05.021>.
60. Bagh, T.; Naseer, M.M.; Khan, M.A.; Pyłacz, P.; Oláh, J. Sustainable growth rate, corporate value of US firms within capital and labor market distortions: The moderating effect of institutional quality. *Oeconomia Copernic.* **2023**, *14*, 1211–1255. <https://doi.org/10.24136/oc.2023.036>.
61. Chen, S.; Duan, D.; Wang, H. Industrial Robots, Factor Market Distortion, and Productivity. *Manag. Decis. Econ.* **2025**, *46*, 1093–1107. <https://doi.org/10.1002/mde.4422>.
62. Bharany, S.; Sharma, S.; Khalaf, O.I.; Abdulsahib, G.M.; Al Humaimedy, A.S.; Aldhyani, T.H.; Maashi, M.; Alkahtani, H. A systematic survey on energy-efficient techniques in sustainable cloud computing. *Sustainability* **2022**, *14*, 6256. <https://doi.org/10.3390/su14106256>.
63. Cavalcante, I.M.; Frazzon, E.M.; Forcellini, F.A.; Ivanov, D. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *Int. J. Inf. Manag.* **2019**, *49*, 86–97. <https://doi.org/10.1016/j.ijinfomgt.2019.03.004>.
64. Jia, X. Digital economy, factor allocation, and sustainable agricultural development: The perspective of labor and capital misallocation. *Sustainability* **2023**, *15*, 4418. <https://doi.org/10.3390/su15054418>.
65. Zheng, X.; Zou, F.; Liu, Z.; Nepal, R. How does digitalization affect capacity utilization in the energy sector? Evidence from China. *Energy Econ.* **2025**, *144*, 108337. <https://doi.org/10.1016/j.eneco.2025.108337>.
66. Amin, N.; Shabbir, M.S.; Pan, Y.; Asif, M. Beyond Growth: The Triple Green Strategy (Green Energy, Green Innovation, and Green Finance) for Sustainable Emissions Reduction in BRICS Countries. *Sustain. Dev.* **2025**, *33*, 5567–5586. <https://doi.org/10.1002/sd.3411>.
67. Zheng, L.; Cao, Y.; Umar, M.; Wang, X.; Safi, A. Environmental policy, digital economy, and green innovation: Navigating the low-carbon transition in emerging seven economies. *Econ. Chang. Restruct.* **2025**, *58*, 67. <https://doi.org/10.1007/s10644-025-09893-0>.
68. Feng, Y.; Yuan, H.; Liu, Y.; Zhang, S. Does new-type urbanization policy promote green energy efficiency? Evidence from a quasi-natural experiment in China. *Energy Econ.* **2023**, *124*, 106752. <https://doi.org/10.1016/j.eneco.2023.106752>.
69. Song, M.; Pan, H.; Shen, Z.; Tamayo-Verleene, K. Assessing the influence of artificial intelligence on the energy efficiency for sustainable ecological products value. *Energy Econ.* **2024**, *131*, 107392. <https://doi.org/10.1016/j.eneco.2024.107392>.
70. Cai, S. Impact of digitization on green economic recovery: An empirical evidence from China. *Econ. Change Restruct.* **2023**, *56*, 3139–3161. <https://doi.org/10.1007/s10644-022-09473-6>.
71. Yang, K.; Kuang, J. How artificial intelligence applications enhance enterprise green total factor productivity? A perspective on human-machine matching and labor skill structure. *Econ. Anal. Policy* **2025**, *87*, 926–947. <https://doi.org/10.1016/j.eap.2025.06.044>.
72. Sreenu, N. The role of digital finance and financing barriers in green innovation: A Study of India. *Econ. Chang. Restruct.* **2025**, *58*, 82. <https://doi.org/10.1007/s10644-025-09923-x>.
73. Meng, C.; Lin, Y. The impact of supply chain digitization on the carbon emissions of listed companies—A quasi-natural experiment in China. *Struct. Chang. Econ. Dyn.* **2025**, *73*, 392–406. <https://doi.org/10.1016/j.strueco.2025.02.007>.
74. Jiang, Y. Government digital governance and corporate green total factor productivity. *Int. Rev. Econ. Financ.* **2025**, *102*, 104338. <https://doi.org/10.1016/j.iref.2025.104338>.

75. Du, Y.; Chen, S. Going for sustainability: How digital transformation affects corporate radical green innovation in China. *Econ. Chang. Restruct.* **2026**, *59*, 14. <https://doi.org/10.1007/s10644-025-09951-7>.
76. Tian, H.; Zhao, L.; Li, Y.; Wang, W. Can enterprise green technology innovation performance achieve “corner overtaking” by using artificial intelligence?—Evidence from Chinese manufacturing enterprises. *Technol. Forecast. Soc. Chang.* **2023**, *194*, 122732. <https://doi.org/10.1016/j.techfore.2023.122732>.
77. Zeng, M.; Zhang, W. Green finance: The catalyst for artificial intelligence and energy efficiency in Chinese urban sustainable development. *Energy Econ.* **2024**, 107883. <https://doi.org/10.1016/j.eneco.2024.107883>.
78. He, G.; Wang, S.; Zhang, B. Watering down environmental regulation in China. *Q. J. Econ.* **2020**, *135*, 2135–2185. <https://doi.org/10.1093/qje/qjaa024>.
79. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [https://doi.org/10.1016/s0377-2217\(99\)00407-5](https://doi.org/10.1016/s0377-2217(99)00407-5).
80. Chen, W.; Meng, Y. Intercity carbon compensation mechanism based on value-added captured responsibility allocation. *J. Environ. Manag.* **2024**, *371*, 123091. <https://doi.org/10.1016/j.jenvman.2024.123091>.
81. Zarrin, M.; Brunner, J.O. Analyzing the accuracy of variable returns to scale data envelopment analysis models. *Eur. J. Oper. Res.* **2023**, *308*, 1286–1301. <https://doi.org/10.1016/j.ejor.2022.12.015>.
82. Oh, D. A global Malmquist-Luenberger productivity index. *J. Product. Anal.* **2010**, *34*, 183–197. <https://doi.org/10.1007/s11123-010-0178-y>.
83. Dong, F.; Li, Y.; Gao, Y.; Zhu, J.; Qin, C.; Zhang, X. Energy transition and carbon neutrality: Exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. *Resour. Conserv. Recycl.* **2022**, *177*, 106002. <https://doi.org/10.1016/j.resconrec.2021.106002>.
84. Hou, Y.; Yang, M.; Li, Y. Coordinated effect of green expansion and carbon reduction: Evidence from sustainable development of resource-based cities in China. *J. Environ. Manag.* **2024**, *349*, 119534. <https://doi.org/10.1016/j.jenvman.2023.119534>.
85. Xu, J.; Yang, B.; Yuan, C. The impact of supply chain digitalization on urban resilience: Do industrial chain resilience, green total factor productivity and innovation matter? *Energy Econ.* **2025**, *145*, 108443. <https://doi.org/10.1016/j.eneco.2025.108443>.
86. Hsieh, C.T.; Klenow, P.J. Misallocation and manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. <https://doi.org/10.1162/qjec.2009.124.4.1403>.
87. Luo, S.; Xiong, Z.; Liu, J. How does supply chain digitization affect green innovation? Evidence from a quasi-natural experiment in China. *Energy Econ.* **2024**, *136*, 107745. <https://doi.org/10.1016/j.eneco.2024.107745>.
88. Ai, H.; Tan, X.; Mangla, S.K.; Emrouznejad, A.; Liu, F.; Song, M. Renewable energy transition and sustainable development: Evidence from China. *Energy Econ.* **2025**, *143*, 108232. <https://doi.org/10.1016/j.eneco.2025.108232>.
89. Huang, M.; Li, Q.; Li, B. From algorithms to green growth: Can artificial intelligence drive enterprise energy transformation? *Econ. Anal. Policy* **2025**, *85*, 1846–1866. <https://doi.org/10.1016/j.eap.2025.02.029>.
90. Stock, J.H.; Yogo, M. Testing for Weak Instruments in Linear IV Regression. 2002. Available online: https://www.nber.org/system/files/working_papers/t0284/t0284.pdf (accessed on 29 January 2026).
91. Tang, Y.; Wang, B.; Pan, N.; Li, Z. The impact of environmental information disclosure on the cost of green bond: Evidence from China. *Energy Econ.* **2023**, *126*, 107008. <https://doi.org/10.1016/j.eneco.2023.107008>.
92. Zhang, D.; Kong, Q. Green energy transition and sustainable development of energy firms: An assessment of renewable energy policy. *Energy Econ.* **2022**, *111*, 106060. <https://doi.org/10.1016/j.eneco.2022.106060>.
93. Fang, C.; Yuan, Y.; Chen, J.; Gao, D.; Peng, J. Examination of green productivity in China’s mining industry: An in-depth exploration of the role and impact of digital economy. *Sustainability* **2024**, *16*, 463. <https://doi.org/10.3390/su16010463>.
94. Liu, Y.; Zhang, Y. An analysis of the influence and mechanisms of the digital economy on the disparities in urban total factor productivity. *Technol. Econ. Dev. Econ.* **2025**, *31*, 1065–1092. <https://doi.org/10.3846/tede.2025.22638>.
95. Wen, S.; Jia, Z. Resource curse or resource blessing: Perspective on the nonlinear and regional relationships in China. *J. Clean. Prod.* **2022**, *371*, 133491. <https://doi.org/10.1016/j.jclepro.2022.133491>.
96. Wang, K.; Chen, B.; Li, Y. Technological, process or managerial innovation? How does digital transformation affect green innovation in industrial enterprises? *Econ. Chang. Restruct.* **2024**, *57*, 10. <https://doi.org/10.1007/s10644-024-09598-w>.
97. Si, R.; Wang, Y.; Cao, M.; Wen, H. Does green technology innovation promote green economic growth?—Examining regional heterogeneity between resource-based and non-resource-based cities. *Int. Rev. Econ. Financ.* **2024**, *94*, 103406. <https://doi.org/10.1016/j.iref.2024.103406>.
98. Tiwari, S.; Mohammed, K.S.; Balsalobre-Lorente, D. Green Finance: A Pathway to Achieving Carbon Neutrality and Sustainable Development. *Sustain. Dev.* **2025**, *33*, 988–1002. <https://doi.org/10.1002/sd.70047>.

99. Tang, J.; Li, W.; Hu, J.; Ren, Y. Can government digital transformation improve corporate energy efficiency in resource-based cities? *Energy Econ.* **2025**, *141*, 108043. <https://doi.org/10.1016/j.eneco.2024.108043>.
100. Liu, Y.; Lin, Y.C. Converting knowledge into Productivity: The role of intellectual property empowerment and digital economy in enhancing regional new quality productivity forces-Evidence from China. *Int. Rev. Econ. Financ.* **2025**, *102*, 104316. <https://doi.org/10.1016/j.iref.2025.104316>.
101. Xia, L.; Han, Q.; Yu, S. Industrial intelligence and industrial structure change: Effect and mechanism. *Int. Rev. Econ. Financ.* **2024**, *93*, 1494–1506. <https://doi.org/10.1016/j.iref.2024.04.002>.

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