Energy Strategy Reviews 52 (2024) 101347

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Smarter and cleaner: How does energy digitalization affect carbon productivity?

Ziyi Shi [a,*], Lawrence Loh [b], Hongshuang Wu [c], Dongri Han [c]

[a] School of Economics and Management, Harbin Engineering University, Heilongjiang, 150001, China
[b] Centre for Governance and Sustainability, NUS Business School, National University of Singapore, Singapore, 117592, Singapore
[c] School of Business, Shandong University of Technology, Zibo, 255012, China

A R T I C L E I N F O

Handling Editor: Dr. Mark Howells

Keywords:
Energy digitalization
Carbon productivity
Nature language processing
Spatial Markov chain
SBM-DDF

A B S T R A C T

Digitalization is a driving force behind the ongoing energy industrial revolutions, catalyzing China's pursuit of carbon neutrality and sustainable development. Leveraging provincial data and annual reports from energy enterprises in China, this study constructs a comprehensive analytical framework that encompasses benchmark regression models, mediating effect models, threshold models, and spatial econometric models. These models are utilized to investigate the multi-faceted impacts of energy digitalization on carbon productivity (CP). The aim is to furnish micro-level evidence and policy guidance for advancing energy transformation and fostering low-carbon development enriched with digital elements. This research employs natural language processing and machine learning techniques to compute an Energy Digitalization Index, examining two critical dimensions: digital industry investment and the inclination toward digital transformation. The following key findings emerge: firstly, energy digitalization (ED) exhibits a statistically significant ability to enhance regional CP, a phenomenon marked by temporal and regional variations. Secondly, the analysis confirms the transmission mechanisms associated with energy technology innovation, energy structure, and energy utilization efficiency, as revealed through the Logarithmic Mean Divisia Index (LMDI) decomposition method. Furthermore, the optimal effect of energy digitalization on low-carbon economies materializes in settings characterized by mature market conditions, modest environmental regulations, advanced digital infrastructure, and reduced resource dependency. Additionally, the spatial Markov chain analysis unveils a conspicuous spatial distribution pattern termed "club convergence" in regional CP, accompanied by a pronounced "Matthew effect." According to the spatial Durbin model, energy digitalization generates favorable spatial spillover effects, primarily in peripheral regions, with a more pronounced short-term influence. Building upon these insights, this paper presents pertinent policy recommendations encompassing the national "digital energy" strategy, regional differentiation policies, and initiatives to stimulate digital technology innovation among enterprises. Our findings furnish robust empirical evidence and constructive policy insights, empowering governments to forge a smarter and cleaner energy ecosystem. Furthermore, these findings offer valuable guidance for other developing nations seeking to implement effective digital strategies.

1. Introduction

The contemporary world confronts a myriad of global challenges encompassing economic stagnation, energy security concerns, and the ever-pressing climate crisis [1]. The Sustainable Development Goals (SDGs) of the United Nations have long beckoned nations to establish accessible, dependable, and sustainable modern energy sources (SDG7 - Affordable and Clean Energy) while simultaneously urging immediate action to combat climate change (SDG13 - Climate Action). In this context, the low-carbon economy stands as a pivotal approach to harmonize socioeconomic growth, ensure energy security, and confront climate change—a consensus embraced by nations across the globe [2]. Among these nations, China, recognized as the world's largest energy consumer and carbon emitter, has set its sights on achieving carbon neutrality by 2060, which necessitates a comprehensive and profound economic transformation. Significantly, the energy sector, the most significant contributor to carbon emissions and a linchpin of the national economy, has emerged as the epicenter of efforts to catalyze a

* Corresponding author.
E-mail address: szy18810294913@163.com (Z. Shi).

https://doi.org/10.1016/j.esr.2024.101347
Received 28 September 2023; Received in revised form 31 January 2024; Accepted 19 February 2024
Available online 28 February 2024

low-carbon economy [3]. Nevertheless, numerous obstacles persist within China's energy industry, including mounting environmental resource constraints, imbalances in energy structures, and the persistence of low-level energy technologies—challenges that collectively amplify the complexity of carbon reduction efforts [4].

In the era of the digital economy, digitalization has demonstrated significant potential for carbon reduction by promoting the optimization of industrial structures, facilitating technological innovation, and reducing energy intensity. As the latent power of digitalization continues to be harnessed, various actors at macro, meso, and micro levels have embarked on the journey of digitalization. Notably, industrial digitalization has emerged as an inexorable trend within the current wave of technological revolution and industrial reform [5]. China's "14th Five-Year Plan for Digital Economy Development" and "14th Five-Year Plan for Modern Energy System" both underscore the pivotal role of digitalization in the energy sector, positioning it as the "sixth energy" following the "fifth energy - energy conservation" [6]. Energy digitalization is heralded as a profound industrial revolution, with data as its core production factor, digital technology as the primary driver, and digital transformation as its new vehicle [7]. From the perspective of sustainable energy development, scholars have substantiated that the application of digital technology in the energy sector can mitigate energy poverty [8], bolster energy security [9], resolve the conundrum of the energy triangle [10], and propel energy transformation [11]. Conversely, the convergence of digital technology and the energy industry has proven instrumental in stimulating economic growth, thereby enhancing energy efficiency [12], fostering technological innovation [13], and fortifying corporate resilience [14]. Undoubtedly, energy digitalization (ED) holds the potential to become an indispensable catalyst for advancing the energy sector and modernizing the industrial supply chain. It represents a novel driving force in realizing China's blueprint for "carbon neutrality." Nonetheless, prevailing research often treats "digital" as an external factor in the energy industry's development, predominantly focusing on the influence of digital technology or the digital economy on the energy sector. This approach fails to seamlessly integrate the digital realm with the energy industry, leading to a limited emphasis on the concept of energy digitalization, let alone its quantification. Simultaneously, research concerning the low-carbon impacts of digital transformation is primarily confined to mechanistic analyses and lacks the identification of multi-dimensional influence effects.

In this paper, we employ economic growth theory and digital economy theory to elucidate the intricate relationship between ED and carbon productivity (CP). To accommodate the availability of data and the regional disparities within China, we have selected Chinese inter-provincial panel data spanning from 2012 to 2021 as our research sample for empirical analysis. The pertinent data have been sourced from regional statistical yearbooks and enterprise annual reports, renowned for their credibility and authoritative nature. In our research methodology, we judiciously employ targeted econometric models to discern the impact of different dimensions. Firstly, we scrutinize the direct influence of ED on regional CP through fixed-effect models and instrumental variable methods. Secondly, we explore the intermediary mechanisms through which ED influences CP, focusing on three key aspects: energy technology innovation, energy structure optimization, and enhancements in energy utilization efficiency. Thirdly, we unveil multiple threshold effects contingent on external factors such as marketization, environmental regulations, digital infrastructure, and resource dependency. Finally, we delve into both short-term and long-term spatial spillover effects using the Spatial Durbin Model (SDM).

This paper makes significant contributions to previous studies in four key aspects. Firstly, it firmly recognizes the crucial role of the energy industry in driving low-carbon development. To our knowledge, this study is the first to investigate the impact of energy digitalization on CP within the Chinese context. In measurement, we adopt an innovative approach employing natural language processing and machine learning techniques to estimate the ED index, focusing on two dimensions: digital industry investment and the willingness to embrace digital transformation. This pioneering method provides a fresh perspective on quantifying digitalization within this specialized field. Secondly, we enrich the existing body of knowledge by subdividing the transmission mechanism of digitalization's impact on CP into three distinct facets: energy technology, energy structure, and energy utilization efficiency, building upon the Logarithmic Mean Divisia Index (LMDI) decomposition method. This innovative approach goes beyond conventional interpretations and broadens the theoretical foundation of "digital carbon reduction." Thirdly, instead of solely concentrating on establishing a linear relationship between ED and CP, we meticulously consider the heterogeneity of the external environment, encompassing market dynamics, governmental policies, infrastructure conditions, and resource dependencies. This comprehensive exploration of potential heterogeneous correlations between ED and CP can serve as a blueprint for environmental restructuring, thereby maximizing the positive impact of ED. Fourthly, we employ the Spatial Markov Chain model to elucidate the spatiotemporal dynamics of CP. By integrating spatial and temporal dimensions, we effectively capture the influence of ED on CP in external regions. This approach both complements and extends prior static investigations. Consequently, we propose a series of policy recommendations aimed at harnessing digital opportunities and actively promoting low-carbon development at the national, regional, and enterprise levels. Our fresh insights into the transmission mechanisms provide a novel focal point for policy formulation. The analysis of threshold effects helps delineate the relative disadvantages of regional external environments, facilitating the implementation of dynamic differentiation policies to maximize the low-carbon impact of digital transformation. The revelation of spatial spillover effects in digital carbon reduction promotes regional collaborative initiatives. Additionally, our novel finding that short-term spatial effects are more pronounced accelerates the pace of regional digital transformation peer groups. In conclusion, this paper furnishes compelling evidence regarding the carbon reduction potential of digital energy, contributing to China's "dual carbon" strategy and offering valuable insights for resource-based and developing countries embarking on energy digital transformation initiatives.

The remainder of this article is structured as follows: The subsequent section conducts a comprehensive review of the literature pertaining to ED, economic development, and carbon emissions. Section 3 delineates the theoretical analysis and establishes research hypotheses. In the fourth section, we introduce the econometric models and core variables. Subsequently, Section 5 delves into the empirical results, while the concluding section presents our findings and policy recommendations, discusses limitations, and outlines future research directions.

2. Literature review

2.1. Research on digitalization and economic development

In the era of digitalization, scholarly attention has progressively shifted from the macroeconomic development of the digital economy to the micro-level digitalization of various subjects. Digitalization represents an advanced culmination of communication, information technology, and internet advancements [15]. Within academic discourse, digitalization has been defined from diverse perspectives, encompassing aspects like business models [16], technological transformations [17], and intelligent manufacturing [18]. While the concept of digitalization may not enjoy universal consensus across academic circles, there is a broad consensus regarding its fundamental components. Firstly, digitalization fundamentally reshapes the operational activities of micro-enterprises by applying modern information technology [19]. Secondly, digitalization strongly emphasizes achieving value co-creation, ensuring economies can secure competitive advantages and sustain growth within highly competitive markets [20]. Thirdly, the overarching objective of digitalization lies in elevating the ecological stature of industrial economies [21].

Contemporary scholarly focus centers on the economic ramifications of digitalization, with research falling into three distinct categories: ① Micro Level Impact: Scholars have argued that digitalization integrates data elements into traditional production systems, ushering in “creative changes” in production organizational structures and the real economy’s factor systems, significantly contributing to enterprise productivity [22]. Quantitative methods such as fixed effects models, generalized least squares estimation methods (FGLS), and Blinder-Oaxaca decomposition have been employed to affirm the positive impact of digitalization on productivity in various regions, including South Africa [23], China [24], and Spain [25]. Furthermore, scholars have uncovered the spatial impact of digitization on productivity [26] and explored the nonlinear relationship between these two factors [27]. ② Meso Level Impact: At the meso level, many scholars underscore the pivotal role of digital technology in shaping industrial structural adjustments [28]. In the collaborative development of digital industrialization and industrial digitalization, digital technology consistently propels industrial transformation and upgrading [29]. It is noteworthy that heterogeneity may exist in this regard [30]. For instance, Fu [31] and Kan et al. [32] conducted studies on manufacturing and service industries, respectively, revealing that digitalization significantly impacts capital-intensive industries more than technology-intensive ones. ③ Macro Level Impact: At the macro level, the digital economy exerts a substantial influence on economic development, primarily due to its substantial contribution to the scale of the traditional economy [33]. According to Cai and Niu [34], the added value of the digital economy in China witnessed an average annual growth of 17.72% between 1993 and 2018, becoming a cornerstone of China’s economic development. Zhang et al. [35] have demonstrated that the positive economic growth impact of digitalization is realized by supporting industrial structure upgrades, increasing total employment, and reshaping employment structures.

2.2. Research on digitalization and carbon emission

Within the academic sphere, discussions regarding the influencing factors of carbon emissions have been extensive and typically encompass macro-environmental aspects, including financial development [36], trade activities [37], foreign investment [38], energy-related aspects like energy rent [39] and energy structure [40], as well as technological innovation aspects such as patent support [41] and green innovation [42]. In recent years, with the proliferation of the digital age, an increasing body of research has emerged concerning the environmental effects of digitalization. These studies are categorized into three primary perspectives: inhibition theory, promotion theory, and nonlinear theory. ① Inhibition Theory: This perspective posits that digitalization can foster low-carbon innovation and optimize resource allocation, yielding positive substitution effects on carbon emissions. This view finds support among prominent researchers [43,44]. Additionally, spatial econometric models have been employed to confirm this perspective in spatial geography [45,46]. In terms of the transmission mechanism, relevant studies have primarily engaged in qualitative discussions and quantitative examinations within the realms of promoting technological innovation [47], optimizing industrial structures [48], and enhancing resource allocation efficiency [49]. ② Promotion Theory: This perspective argues that digitalization may counteract carbon emission reduction, offering three essential explanations. Firstly, digitalization often relies on numerous electronic devices and accessories, which possess a higher energy demand throughout their lifecycle, consequently amplifying carbon emissions [50]. Secondly, the “cost effect” of digitalization suggests that the widespread use of ICTs leads to diminished marginal costs, reducing the cost of information while elevating the cost of products and services, thereby diverting funds away from carbon reduction efforts and accelerating carbon emissions [51]. Thirdly, the “energy rebound effect” of digitalization entails that energy efficiency and productivity improvements incentivize the industrial sector to increase production and consume more energy, ultimately leading to greater pollution. ③ Nonlinear Theory: According to this perspective, the relationship between digitalization and carbon emissions is not fixed. Specifically, when the quadratic term of digital transformation is introduced, it exhibits a distinct parabolic pattern [52,53]. After incorporating spatial factors, Li and Wang [54] confirmed the inverted “U"-shaped relationship between the two variables, while Cheng et al. [55] arrived at a contrary conclusion. Moreover, some researchers have unveiled a more intricate connection between the two by constructing panel threshold models. For instance, when digitalization serves as the threshold variable, Hao et al. [56] determined that the influence of digitalization on carbon emissions assumes an inverted “N-type” shape. Conversely, when the threshold variable is energy efficiency, Zhang et al. [57] identified an “N-type” relationship.

2.3. Research on energy digitalization

A comprehensive and authoritative analysis of energy digitalization has yet to crystallize within academia. Scholars have delved into the subject from various perspectives, including organizational digitalization, management digitalization, process digitalization, and product digitalization within energy enterprises and energy systems. Qualitatively, Semeraro et al. [58] employed a literature research method to assess the current digitalization status in energy storage, evaluating aspects such as application environment, life cycle stage, digital twin functionality, and digital twin architecture. Polyanska et al. [59] devised a model grounded in fuzzy set theory to gauge the digitalization maturity of Ukrainian energy companies, encompassing dimensions like strategy, human resources, organizational culture, technology, structure, and marketing, laying the groundwork for energy digitalization. Quantitatively, Park et al. [60] employed an informal academic text analysis coupled with the signal model to investigate the trajectory of ED. Wang et al. [61] established an evaluation index framework for energy digitalization, spanning four dimensions: integration basis, integration conditions, integration applications, and integration performance. Their findings revealed that China’s energy digitalization level has progressively increased, albeit with notable regional disparities. Theoretical explorations underscore the pivotal role of energy digitalization in enhancing energy efficiency [11], driving technological innovation [62], and fortifying enterprise resilience [9]. Notably, it is poised to emerge as a new catalyst propelling economic entities to traverse the Environmental Kuznets Curve (EKC) [63,64].

While existing studies offer promising insights, they exhibit some noteworthy shortcomings. Firstly, most researchers have primarily explored the impact of digitalization on economic development and carbon emissions without considering that China’s economic growth and carbon emissions are not entirely decoupled. This limitation results in an insufficient exploration of the intricate relationship between digitalization and developing a low-carbon economy. Secondly, despite the energy industry’s central role in China’s national economy and its significant contribution to carbon emissions, existing research predominantly focuses on the digitalization of the manufacturing sector, overlooking the specific nuances of energy digitalization. Thirdly, there remains ample room for further investigation into the effects of digitalization. Specifically, examining influencing mechanisms tends to be somewhat rigid, and heterogeneity analyses often fail to fully encompass external environmental adjustments, and spatial effects frequently lack temporal factor decomposition. Lastly, there is a pressing need for refinements in calculating the degree of ED. Presently, digitalization measurement predominantly adopts a regional perspective, leading to a dearth of precise measurements concerning the digitalization of particular industries.

This paper aims to bridge the gaps in the research mentioned above by adopting innovative approaches. We leverage text mining technology with word frequency statistics to evaluate the extent of energy digitalization. Simultaneously, we employ targeted econometric models to explore the multifaceted impacts of energy digitalization on CP. These models include the intermediary effect model, the threshold regression model, and the SDM.

3. Theoretical analysis and research hypothesis

3.1. Direct effect of ED on CP

There is unanimous consensus that Energy Digitalization represents a systematic revolution within the energy sector, facilitating the advancement of high-quality energy development through the deep integration of digital technology and the energy industry. In light of pertinent research, we undertake an analysis of the fundamental essence of ED. We contend that the essence of ED lies in the innovative integration of information technology, operational technology, and electrical technology. Throughout this process, it orchestrates the orderly flow of information, energy, and resources, culminating in a production factor structure intricately intertwined with data and energy. Concurrently, ED empowers traditional production processes, management methodologies, and business models with data-centric elements, giving rise to novel networked production methods and platform-driven industrial organizational forms. It thereby reconstructs the nodes and logic governing the creation and transfer of value within energy enterprises. Ultimately, this transformation optimizes the efficiency of production, operation, and maintenance across the entire energy industry chain. Building upon this foundation, this paper asserts that ED can directly influence CP from three pivotal perspectives: factor structure, industrial organization, and technological advancement.

Viewed through the lens of factor structure, digitalization catalyzes a transformative reconstruction of traditional factor structures, resulting in profound changes to the energy industry's production methods and elevating Green Total Factor Productivity. The data factor, characterized by its non-competitive and non-exclusive nature, has undeniably assumed a pivotal role as a production factor within the digital economy landscape. This development reinforces the conditions for escalating returns to scale and expands the horizons of conventional economic growth theory [65]. Facilitated by the permeability, substitutability, and synergy inherent in digital technology, data elements can exert multiple effects on energy components, including superposition, aggregation, and multiplier effects. Consequently, Energy Digitalization restructures the composition of traditional factors and optimizes resource allocation, thereby facilitating the creation of new economic, social, and environmental values. Moreover, digitalization revamps the production chain, which is evident in the significant enhancements in operational efficiency across the production process. This encompasses resource extraction, production decision-making, equipment operation, product processing, and electricity transportation, consequently diminishing reliance on traditional production modes reliant on natural resources and mitigating environmental pollution [66].

From the perspective of industrial organization, digitization carries the potential to dismantle industrial boundaries and reconfigure traditional industrial organizational structures, thereby expediting CP. Building on the insights of Xiao and Qi [67], digitalization can dismantle the "information islands" among various entities within the industrial value chain. This significantly diminishes transaction costs, weakens industrial boundaries, and deepens the structure of industrial organization, nurturing an interconnected ecological community characterized by cohesion. Digitalization gives rise to a decentralized, networked industrial ecosystem encompassing all facets of the energy industry, thereby dismantling spatial and temporal limitations. This augmentation strengthens the synergistic impact of subdivided industries, elevates the operational efficiency of energy systems, and paves the way for progressive, streamlined, and low-carbon energy industry development [68].

From the vantage point of technological progress, digitalization underpins the transition of both the economy and society towards digitization, intellectualization, and low-carbonization facilitated by cutting-edge digital technologies. On the one hand, digital, operational, and electrical technology convergence engenders novel energy development models and business paradigms, such as comprehensive intelligent energy services and virtual power plants. The fusion of watt-flow and bit-flow propels the shift from the traditional linear production chain model to a networked collaborative parallel mode [69]. This transition empowers the energy sector to optimize resource allocation and enhance CP. On the other hand, digital technologies are intricately interwoven with the energy production cycle, encompassing generation, transmission, distribution, storage, and utilization. Through mechanisms like carbon footprint monitoring, carbon data analysis, and carbon-neutral deductions, digitalization offers substantial advantages for bolstering the green transformation of production, consumption, and end-user governance [70]. This, in turn, mitigates carbon emissions without compromising economic output. Consequently, this paper posits Hypothesis 1.

Hypothesis 1. ED can directly promote CP.

3.2. Indirect effect of ED on CP

When energy is included in the endogenous economic growth model, the Cobb-Douglas production function for the final production sector can be expressed as $Y = A \bullet K^a \bullet L^b \bullet E^c$. Here, A is technological progress, K、L and E refer to the capital, labor, and energy, and a、b and c indicate the share of each factor, respectively. Meanwhile, the emission of carbon dioxide C can be described as the product of carbon emission coefficient τ and fossil energy consumption E_f: $C = \tau \bullet E_f$ [71]. According to the LMDI model, CP is split into three parts: $\frac{Y}{C} = \frac{Y}{\tau \bullet E_f} = \frac{Y}{E} \times \frac{E}{E_f} \times \frac{E_f}{C} = eff \times estru \times etech$. Where $\frac{Y}{C}$ indicates carbon productivity, *eff* represents energy utilization efficiency, *estru* refers to the energy structure, $\frac{E_f}{C} = \tau^{-1}$ relies on the energy technology progress *etech*. Based on the above decomposition, this paper will analyze the influence mechanisms of ED affecting CP through energy technology, energy structure, and energy utilization efficiency.

3.2.1. The mediating role of energy technology innovation

Li et al. [72] noted that energy technology innovation seeks to develop new energy sources while simultaneously promoting the conservation and purification of fossil energy. Numerous studies have underscored the role of energy technology innovation in reducing pollution and enhancing CP [73,74]. Within this study, we contend that the unique advantages of digitalization within the platform ecosystem can foster a conducive ecological environment for energy technology innovation. Equipped with a robust innovation-oriented function, digitalization continuously elevates the caliber of energy technology innovation, expediting CP. To begin with, the advantages of digitalization in information collection, matching, and analysis can transcend temporal and spatial limitations on disseminating non-material resource elements such as information and knowledge. Reducing information tracking costs and mitigating information asymmetry provide the foundational prerequisites for energy technology innovation [75]. Secondly, digitalization amplifies the competitive market dynamics for energy enterprises. Drawing from signal theory, the exigent external environment fosters competition among energy firms striving for "green and smart energy." This competition serves as a stimulus for the output of energy technology innovation [44] and propels the adoption of green technology, thereby driving CP to a certain extent. Lastly, the network platform attributes inherent in digitalization facilitate the establishment of an innovation cooperation network among the energy industry, research institutions, and universities and cultivate an innovation ecosystem spanning production, consumption, and government sectors. This linkage between innovation output and application enhances the sustainability and relevance of energy technology innovation.

3.2.2. The mediating role of energy structure

Renewable energy sources are widely recognized for their environmental friendliness and low carbon footprint. The transition towards a cleaner energy structure dominated by renewable sources holds the potential to mitigate the adverse environmental externalities associated with fossil fuels and generate substantial positive externalities. This transition reduces carbon intensity and fosters CP [76]. The broad technological advancements and innovations associated with digitalization play a pivotal role in dismantling the barriers within the new energy industry, thereby expediting the shift towards a cleaner energy structure and enhancing CP [77]. On the supply side, integrating digital technology with new energy technologies optimizes various facets of the new energy sector, including construction, operations and maintenance, power generation, and energy storage. This optimization contributes to the sustainability, stability, and predictability of new energy generation [78], thereby propelling the growth of new energy. For instance, digital technologies enable the aggregation of distributed energy sources like wind and photovoltaic power into virtual power plants, facilitating multi-energy complementarity and flexible distribution. On the demand side, integrating digital technology within New Energy Vehicles (NEVs) has given rise to multiple functions such as intelligent driving, networking, and sharing. These functions enhance user convenience, efficiency, and safety, resulting in heightened consumer demand and expanding the application scale of new energy sources. Regarding the alignment of supply and demand, the fusion of artificial intelligence technology and algorithmic models enables efficient management and precise matching of energy supply from generation to demand. This addresses the consumption and storage challenges associated with renewable energy, thereby expediting the transition from traditional power generation to new energy generation [79].

3.2.3. The mediating role of energy utilization efficiency

Energy utilization efficiency is paramount to achieving CP with maximum economic benefits and minimal energy consumption [80]. Digitalization gives rise to an energy interconnection paradigm underpinned by platforms and driven by intelligence, optimizing energy efficiency across the entire spectrum, from power generation to electricity consumption. On the one hand, Energy Digitalization amalgamates electricity technology with digital technology, sparking a new era of managing energy at the terawatt level. This breakthrough bridges the gap between each node in the "power generation - transmission - distribution - storage – utilization" process, ushering in digitalization and intellectualization of the entire energy chain. Consequently, this improves the efficiency of power generation, operation, maintenance, and utilization.

On the other hand, ED transitions from supply-oriented large-scale production to user-driven customized production. This shift significantly enhances the efficiency of supply-demand matching, leading to energy-saving effects [81] and a notable improvement in energy utilization efficiency. In light of these considerations, we posit the following assumption.

3.3. Threshold effect of ED on CP

Metcalfe's Law suggests a potential nonlinear relationship between Energy Digitalization and regional CP [82]. In essence, the impact of digitalization may exhibit variations among provinces, particularly given China's marked regional disparities in development. With this perspective in mind, we aim to comprehensively examine the external factors shaping digitalization, encompassing the regulatory roles played by the market, government, and digital infrastructure.

3.3.1. The regulatory role of market adjustment

Marketization is recognized as a pivotal external institutional factor acting as a "catalyst" for the low-carbon economy effect of Energy Digitalization [83]. This effect is multifaceted. Firstly, a more mature factor market facilitates the seamless integration, synergy, and evolution of data factors with traditional factors. This expedites the process of capitalizing on data and unlocks the dividends of data factors [65]. Consequently, the energy sector becomes intricately entwined with the digital economy, amplifying the low-carbon economy effect of ED. Secondly, a heightened emphasis on product marketing often coexists with a more competitive external business landscape. This competitive pressure not only compels enterprises to engage in technological innovation but also stimulates the efficient allocation of resources driven by profit motives. Consequently, the digitalization process accelerates, enhancing green productivity. However, it is imperative to acknowledge that economies with less market-based systems may experience immature market mechanisms. This imbalance between government regulation and market adjustments can impede the flow of production materials, hinder the adoption of digital technologies, and disrupt market competition [84]. Consequently, this limitation can curtail the beneficial impact of ED on CP.

3.3.2. The regulatory role of environmental regulation

The concept of the weak Porter hypothesis posits that moderate environmental regulation can foster innovation revolutions. In cases where regional environmental regulation strikes an appropriate balance, it can give rise to what is known as an "innovation compensation effect" [85]. This effect stimulates innovation in low-carbon and digital technologies, propelling digitalization and low-carbon transformation within the energy industry, consequently positively impacting CP. However, overly stringent environmental regulations can lead to what is termed an "innovation extrusion effect" [86]. Such regulations increase the cost of pollutant emissions, thereby tightening the financial constraints on digitalization. This hindrance impedes the adoption and dissemination of digital technologies within the energy sector, limiting the full potential of Energy Digitalization to enhance CP.

3.3.3. The regulatory role of digital infrastructure

Digital infrastructure can be likened to fertile "soil" for digitalization [11]. It represents the convergence of cutting-edge Information and Communication Technology (ICT) with traditional infrastructure, giving rise to various digital platforms for businesses and government operations. This synthesis combines the conventional infrastructure's public service attributes with the data-driven qualities of digitization, intelligence, and networking. Regions with advanced digital infrastructure, including technologies such as 5G networks, cloud computing platforms, and artificial intelligence, boast a robust array of intelligent tools and technological resources. This fosters the efficient flow of information and resources within these areas, enabling a profound penetration of digital technology into the energy sector. Consequently, ED exerts a more pronounced impact on CP in these regions. In contrast, regions lacking adequate digital infrastructure cannot provide a conducive technical environment for digitalization [87]. This limitation diminishes the influence of ED on CP within these areas.

3.3.4. The regulatory role of resource dependence

In line with the resource curse hypothesis, regions with high resource dependence tend to be dominated by resource exploitation and processing industries characterized by high energy consumption and pollution [88]. Over time, these areas often develop a rigid and extensive economic model, making transitioning toward an improved CP challenging. Moreover, the persistence of natural resources in resource-based regions can crowd out high-end factors such as technology and human capital [89], hampering regional disruptive innovation and digital transformation efforts, thereby making it difficult to demonstrate the carbon reduction effect of digital transformation. Conversely, regions with low resource dependence experience more significant constraints related to resource endowments in their economic development models. This implies greater flexibility in the flow of factors and changes in industrial structure, ultimately facilitating a more positive impact of digital transformation on CP. Consequently, we propose Hypothesis 3.

Hypothesis 3. The impact of ED on CP is regulated by the market, government, digital infrastructure, and resource dependence. The positive effect is more remarkable under a higher marketization degree, moderate environmental regulation level, advanced digital technology facilities, and weaker resource dependence.

3.4. Spatial effect of ED on CP

As a result of the sharing and permeability of digital technology, critical resources like technology and knowledge have been freed from geographical constraints and industry-specific barriers, leading to the superposition effect of “mobile space” and “mobile industry.” Consequently, it is anticipated that the positive impacts of ED on the low-carbon economy will extend beyond individual regions. Scholars have previously explored the spatial effects of digitalization on both carbon emissions and economic outcomes separately [54,90]. This paper posits that ED can benefit CP in neighboring regions through two mechanisms: interregional low-carbon technology spillover and the strategic coordination of digital transformation. On the one hand, following Marshall’s theory of externalities and Romer’s model of knowledge spillover growth [91], it is understood that technology possesses externalities and can spill over to neighboring regions. Through digital technology, ED can potentially empower low-carbon technology innovation in geographically adjacent areas by expediting the flow of innovation factors across time, thereby laying the technical groundwork for collaborative CP improvement.

On the other hand, as energy companies within a region increasingly adopt ED practices, they may serve as a source of demonstration and peer effects for energy firms in neighboring regions, inspired by the positive feedback related to environmental and economic performance [92]. Driven by information dissemination, competitive emulation, and value internalization, energy enterprises in nearby regions are likely to implement their digital strategies, ultimately highlighting the low-carbon economic benefits of digitalization. Consequently, we propose the final hypothesis.

Hypothesis 4. ED can exert a beneficial effect on CP in external regions.

To sum up, Fig. 1 presents the diagram of the theoretical model, and Fig. 2 displays the diagram of the theoretical framework in this paper.

4. Methodology

4.1. Model construction

Constructing appropriate models is crucial to test the four hypotheses outlined earlier empirically. Based on relevant literature, we have chosen specific models to examine the multidimensional impact of energy digitalization on CP. The literature-based rationale for our model selection is summarized in Table 1. We observe that in the field of research on digitalization, the low-carbon economy, and green development, scholars have focused on various aspects, including direct effects, indirect effects, nonlinear effects, and spatial effects. Regarding direct effects, applying the two-way fixed effects model is predominant, with some scholars employing IV-2SLS and GMM to address endogeneity concerns. Accordingly, this paper constructs a fixed effect model combined with the instrumental variable method to test the direct effect proposed in H1.

Regarding indirect effects, existing research utilizes mediating effect models based on two-stage or three-stage regression methods. These mediating variables encompass industrial structure, technological innovation, and energy intensity. Therefore, we adopt a three-stage stepwise regression-based mediating effect model to rigorously assess the indirect effect posited in H2, supported by mathematical evidence. Furthermore, it is evident that previous research primarily employs threshold panel models to investigate nonlinear effects. These models operate on the idea that when a specific economic parameter reaches a certain threshold, another economic parameter undergoes a structural break. The critical value for this transition is termed the threshold value. As such, we employ a threshold regression model to examine the nonlinear effect postulated in H3. To evaluate spatial effects outlined in H4, we construct a spatial econometric model, as widely applied by most scholars in the field. This model introduces a spatial weight matrix and spatial correlation coefficient, allowing us to determine the elasticity coefficients of variables within geographical space.

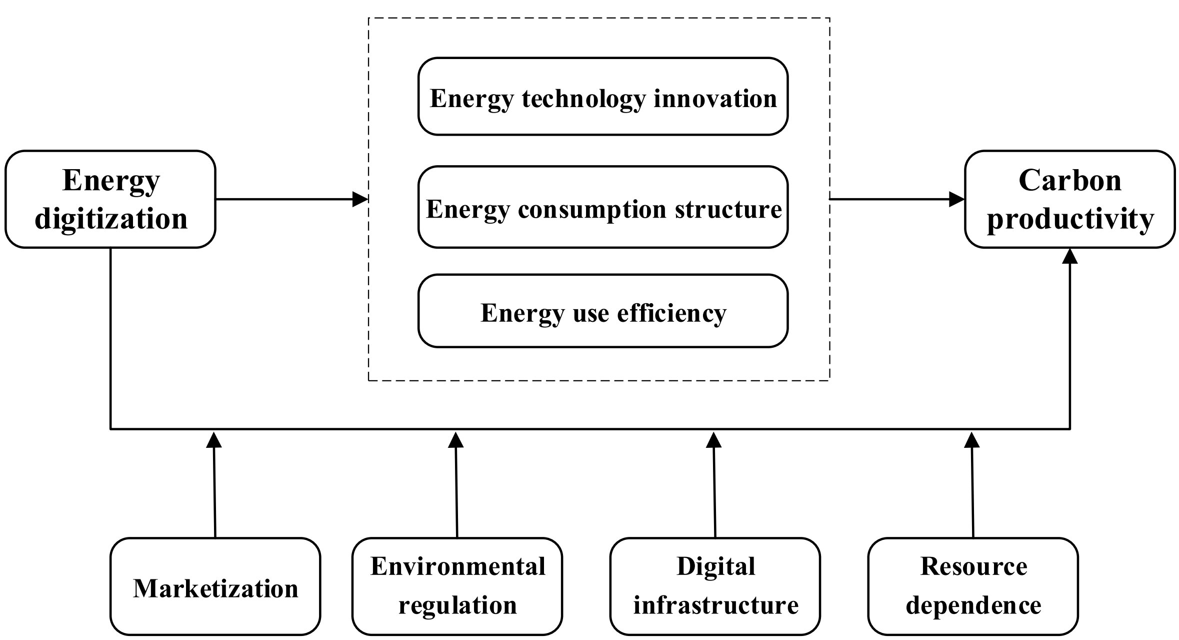

Fig. 1. The diagram of the theoretical model.

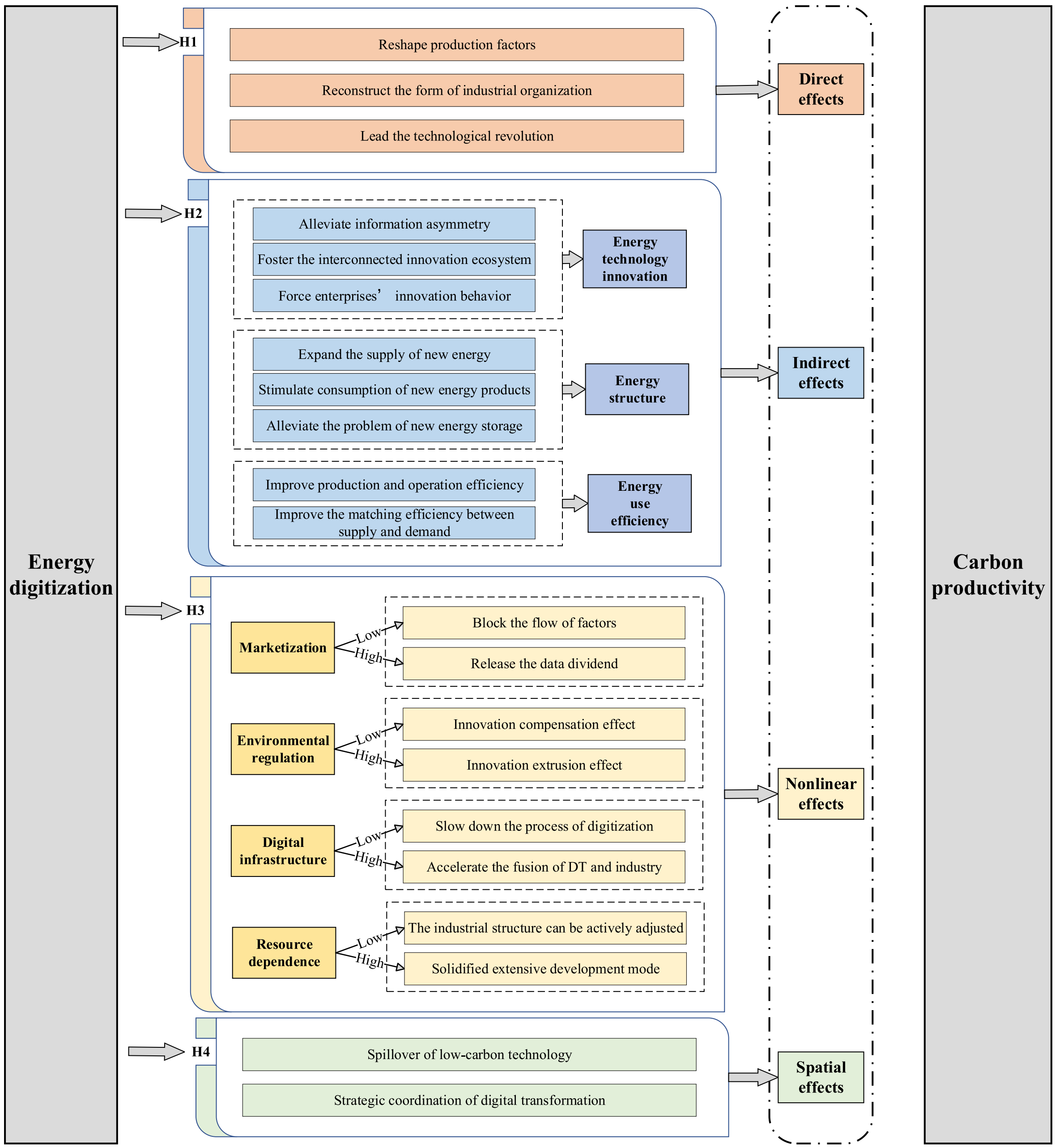

Fig. 2. The diagram of the theoretical framework.

4.1.1. Benchmark model

This article integrates energy digitalization into the research framework of CP to test hypothesis 1 and establishes baseline models using pooled ordinary least squares (POLS), random effects (RE), and fixed effects (FE). The equation is as follows:

$$cp_{it} = \alpha_0 + \alpha_1 enerdig_{it} + \alpha_2 fdi_{it} + \alpha_3 size_{it} + \alpha_4 city_{it} + \alpha_5 ins_{it} + \alpha_6 trans_{it} + \lambda_i + \varepsilon_{it} \tag{1}$$

Where them, cp_{it} is considered as the explained variable, presenting the carbon productivity of region i during the period of t, $enerdig_{it}$ expresses the degree of energy digitalization. Control variables cover foreign direct investment fdi_{it}, the scale of industrial enterprise $size_{it}$, the level of urbanization $city_{it}$, industrial structure ins_{it} and the level of transportation infrastructure $trans_{it}$. In addition, α_0 is the intercept term, α_n is the parameter to be estimated, λ_i refers to the unknown individual effects and ε_{it} indicates the random error.

4.1.2. Mediation effect model

To examine hypothesis 2, mediation effect models are further constructed. Following the approach outlined by Wen and Ye [99], a three-step regression model is developed as the benchmark.

$$mediation_{it} = \beta_0 + \beta_1 enerdig_{it} + \beta_n X_{it} + \lambda_i + \varepsilon_{it} \tag{2}$$

$$cp_{it} = \omega_0 + \omega_1 enerdig_{it} + \omega_2 mediation_{it} + \omega_n X_{it} + \lambda_i + \varepsilon_{it} \tag{3}$$

Where, $mediation_{it}$ is selected as energy technology innovation (*enerinno*), energy structure optimization (*enerstru*), energy utilization efficiency (*enereffi*); β_0 and ω_0 are intercept terms; β_1 and ω_1 indicate the parameters to be estimated; β_n and ω_n refer to the parameter vectors to be estimated. X_{it} contains a variable group formed by a series of control variables in Formula (1). The other parameters are the same as above.

Table 1
Literature basis for model building.

Topic	Effects Type	Sample	Model	Variables
Digitalization and carbon emissions [52]	Direct effect Indirect effect	30 provinces in China from 2006 to 2019	Fixed effect model + IV-2SLS Mediating effect model	Intermediate variable： Energy structure, Industry structure, technology innovation
Digital economy and carbon emission [54]	Indirect effect Spatial effect	274 prefecture-level cities and above in China from 2011 to 2018	Spatial Durbin model Mediating effect model	Intermediate variable： Energy use, green technology progress, industrial structural upgrade
Digital economy and carbon emission [93]	Direct effect Indirect effect	60 countries from 2008 to 2019	Double fixed effects model + GMM Mediating effects model	Intermediate variable： Economic growth, industrial structure, financial development
Digitalization and total factor carbon performance [94]	Direct effect Indirect effect	274 prefecture-level cities and above in China from 2003 to 2019	Double fixed effects model Single step regression	Intermediate variable： Industrial structure, green technological innovation, energy efficiency
Digitalization and carbon emissions [95]	Direct effect	55 countries from 1996 to 2019	Fixed effects model + OLS	–
digital finance and green development [96]	Direct effect Indirect effect Threshold effect	238 prefecture-level cities in China from 2012 to 2021	Fixed effect model Mediation effect model Threshold regression model	Intermediate variable： green technology innovation Threshold variable： digital finance
Digitalization and green development [47]	Direct effect Indirect effect Spatial effect Threshold effect	278 cities in China from 2011 to 2019	Fixed effect model Mediating effect model Spatial Durbin model Threshold panel model	Intermediate variable： economic openness, industrial structure, market potential Threshold variable： economic openness, industrial structure, market potential
Digital economy and sustainable development [97]	Direct effect Indirect effect Threshold effect	286 cities in China from 2011 to 2019	Fixed effect model + IV-2SLS Mediating effect model Threshold panel model	Intermediate variable： green technological innovation, human capital Threshold variable： environmental regulation
Digital transformation and total factor carbon productivity [62]	Direct effect Threshold effect	30 provinces in China from 2009 tp 2019	Fixed effect model Threshold regression model	Threshold variable: Technological innovation
Trade fdi and CO2 emissions [98]	Spatial effect Threshold	18 Latin American countries from 1970 to 2019	Spatial Durbin model,	–

4.1.3. Threshold regressive model

To provide evidence for Hypothesis 3, we construct the threshold regression model proposed by Hansen [100]. In the model, marketization (*market*), environmental regulation (*regulation*), digital infrastructure (*diginfra*), and resource dependence (*ependence*) are taken as heterogeneous variables. The econometric model is established as follows:

$$
\begin{aligned}
cp_{it} = {} & \theta_0 + \theta_1 enerdig_{it} \times I(threshold_{it} \leq \eta) \\
& + \theta_2 enerdig_{it} \times I(threshold_{it} > \eta) + \theta_n X_{it} + \varepsilon_{it}
\end{aligned} \tag{4}
$$

Where θ_0 is the intercept term; θ_1 and θ_2 indicate the parameters to be estimated; θ_n refers to the parameter vectors to be estimated; $threshold_{it}$ is the threshold variable set in this paper; η is the value of the single threshold. $I(\bullet)$ represents the indicator function. The other parameters are the same as above.

4.1.4. Spatial econometric model

Regarding hypothesis 4, we introduce the SDM, and the formulation is as follows [101]:

$$
\begin{aligned}
cp_{it} = {} & \gamma_0 + \rho W \times lcd_{it} + \gamma_1 enerdig_{it} + \xi_1 W \times enerdig_{it} + \gamma_n X_{it} + \xi_n W \times X_{it} \\
& + \mu_{it}
\end{aligned} \tag{5}
$$

Where γ_0 is the intercept term, ρ represents the spatial autoregressive coefficient, γ_1 and ξ_1 indicate the parameters to be estimated; γ_n and ξ_n refer to the parameter vectors to be estimated. W represents the spatial weight matrix. Since neither geographical distance nor economic distance alone can fully depict the genuine dependency relationship of spatial units, this paper adopts the spatial weight matrix of economic geographic distance regarding Yang et al. [102]. $W \times lcd_{it}$ and $W \times enerdig_{it}$ Two different interaction effects in spatial metrology are represented: the endogenous interaction effect and the exogenous interaction effect. The other parameters are as previously described.

4.2. Variable selection

4.2.1. Dependent variable

Carbon productivity (*cp*). Some scholars use the carbon emission index as a proxy variable for low-carbon development, while others create complex index systems to measure it. However, the former approach overlooks the non-decoupling relationship between carbon emissions and economic benefits at the current technological level, and the latter can lead to conflicting results due to the diversity and complexity of index selection. In essence, developing a low-carbon economy revolves around improving CP [103]. Therefore, this paper aims to construct a multidimensional input-output index system to measure regional CP from an efficiency perspective. To address the "slack" or "crowding" of input elements, this paper employs the Super-SBM-DDF model, which can measure unexpected output related to environmental pollution. We create an output-oriented Malmquist-Luenberger productivity index using MAX DEA Pro software, assuming constant returns to scale. The following input and output indicators have been selected based on the practices of Han et al. [62], as shown in Table 2.

4.2.2. Key independent variable

Energy digitalization (*enerdig*). Some are crucial aspects of this study. Various scholars have adopted different approaches to measure digitalization levels in industries and regions. Some have constructed multidimensional indexes considering digitalization input, application, and

Table 2
The input and output indicators.

Variable	Indicator	Calculation
Input	Human capital	Quantity of employment
	Physical capital	Fixed asset investment
	Energy input	Total energy consumption
Desired output	Economic benefit	Real GDP
Undesired output	Carbon dioxide emission	CEADs

output, while others have focused on measuring regional digitalization based on internet development and digital technology indicators. Additionally, some researchers have employed text analysis of corporate annual reports to estimate the level of digital transformation among micro-level entities. However, these measurement methods have their limitations. Firstly, the strong permeability of digital technology makes it challenging to assess the degree of digitalization in a specific industry accurately. Secondly, the level of digitalization extends beyond just the development of digital technologies [104]. Furthermore, methods that rely on text word frequency analysis can only represent the intention and actions of enterprises in their digital transformation efforts, failing to capture the overall digital scale of an industry.

We believe that energy digitalization goes beyond merely the digitalization of the energy industry or the widespread use of digital technology in a region. It involves creating a green and efficient energy system through the coordinated development of digitalization in the energy industry and digital industrialization. Achieving this goal necessitates substantial digital investment support from the industry and proactive digital strategy guidance from enterprises. Based on this understanding, we adopt the approach of "digital industry investment support - digital transformation strategic guidance" to construct the Energy Industry Digital Transformation Index (ED) as follows:

$$enerdig_{it} = diginput_{it} \times digstrategy_{it} \tag{6}$$

Where $diginput_{it}$ refers to the digital input in the energy industry, represented by the relative consumption coefficient of digital input in the energy industry, as shown in the provincial 42 Departmental input-output tables [105]. Compared to the direct consumption coefficient, the relative consumption coefficient better reflects the importance of the target intermediate input in the production process of a specific industry. Below is the calculation formula.

$$a_{jk} = \frac{x_{jk}}{x_j} \tag{7}$$

$$a_{jd} = \frac{x_{jd}}{x_j}, d \in k \tag{8}$$

$$b_{jd} = \frac{a_{jd}}{\sum_{k=1}^{42} a_{jk}} \tag{9}$$

Where a_{jk} is the direct consumption coefficient of the energy industry j to the intermediate sector k, x_{jk} indicates the actual consumption of intermediate sector k in the production process of the energy industry and x_j represents the total output of the energy industry. Similarly, the paper constructs the direct consumption coefficient of the energy industry to the digital industry sector d. According to the "Statistical Classification of Digital Economy and Its Core Industries (2022)", digital industries include electrical machinery and equipment, communication equipment, computers, and other electronic equipment, as well as information transmission, software, and information technology services. The ratio of a_{jd} to the sum of the direct consumption coefficients of all sectors is obtained as the target value.

Additionally, $digstrategy_{it}$ in formula (6) represents the propensity of micro-level entities towards digital transformation. Drawing from the methodology employed by Zhang et al. [13], this study conducts a quantitative analysis of word frequencies related to "digitalization" within the annual reports of energy enterprises. The data processing involves a four-dimensional approach encompassing securities code, word frequency, province, and year to ascertain the extent of energy digitalization across different provinces. The specific procedure is delineated into five steps: ① Screening of Energy Enterprises: Distinct from sectors like manufacturing and finance, the energy industry lacks a precise delineation, and statistical data regarding energy enterprises in China is fragmented. Consequently, drawing insights from prior research [61,106], we adopt a comprehensive approach to identify publicly listed energy enterprises based on industry classifications within both the national economic framework and the Wind Financial Terminal database. This approach ensures the inclusion of the entire energy industry spectrum, encompassing upstream energy extraction, midstream energy chemicals, and downstream commercial consumption, thereby facilitating a more thorough estimation of the degree of energy digitalization. ② Mining of Enterprise Annual Reports: Leveraging machine learning techniques, this study extracts text content from the annual reports of energy companies spanning from 2012 to 2021. The extraction process is conducted using Python programming. ③ Construction of the Lexicon "Energy Digitalization": Building upon prior research endeavors [92,107], this study establishes a lexicon relevant to energy digitalization. The lexicon comprises two primary dimensions: the technology base and application practice layers. The technology base layer encompasses phrases such as artificial intelligence technology, big data technology, cloud computing technology, and blockchain technology. In contrast, the application practice layer incorporates phrases such as intelligent energy, virtual power grid, energy Internet, smart power grid, and distributed energy. ④ Matching the Lexicon with Annual Report Texts: To quantify the degree of energy digitalization within the annual reports, the text content is meticulously matched against the predefined lexicon. This matching process is facilitated using the Jieba dictionary in the Python programming language, thereby generating word frequency counts related to energy digitalization. ⑤ Calculation of Regional ED Degree: By incorporating securities code, word frequency, province, and year as critical variables, this study derives aggregated summaries of word frequencies and the total number of energy enterprises within each geographical region. Subsequently, the regional ED degree is computed by applying a logarithmic transformation to the word frequency per unit enterprise.

4.2.3. Mechanism variables

① Energy technology innovation (*enerinno*). This category encompasses innovations related to both fossil energy enhancement and renewable energy development, as observed in prior research [108,109]. Building on the methodology employed by Li et al. [72], this study employs the number of patent applications for both types of energy technology as a comprehensive proxy for *enerinno*.

② Energy structure optimization (*enerstru*). The 14th Five-Year Plan for Modern Energy has outlined an ambitious target for China, aiming to achieve a non-fossil energy contribution of approximately 39% in power generation by 2025. The enhancement of clean energy consumption and its electricity generation plays a fundamental role in achieving this energy structure optimization goal [110]. While no authoritative data regarding clean energy consumption in China exists, this study, in line with the approach adopted by Destek and Aslan [111], employs the proportion of non-fossil energy generation as an indicator to characterize energy structure optimization.

③ Energy utilization efficiency (*enereffi*). Measuring the economic benefits of each energy consumption unit, energy utilization efficiency is commonly represented by GDP per unit of energy consumption [43,112].

4.2.4. Threshold variables

① Marketization (*market*). The regional external institutional environment is characterized using the marketization indicator developed by Fan et al. [113]. This indicator encompasses five key dimensions: the development of a non-state-owned economy, the government-market relationship, product market conditions, intermediary organizations, and factor market characteristics. Additionally, necessary adjustments have been made to the marketization index to ensure data comparability across the period from 2012 to 2021 [114].

② Environmental regulation (*regulation*). Regulatory efforts are quantified by the ratio of completed investment in industrial pollution control to the secondary industry's added value, following the approach proposed by Zhang et al. [103].

③ Digital infrastructure (*diginfra*). The digital infrastructure is assessed based on a comprehensive indicator system, incorporating elements such as Internet penetration (the proportion of Internet users in the resident population), telephone penetration (total number of telephones/Total population of administrative area × 100), length of long-distance cable lines, the number of Internet domain names, and broadband access IoT ports, as adopted by Pan et al. [115] and Chen [92]. The digital infrastructure index is ultimately calculated using the entropy method. The steps of the entropy method are as follows:

a Standardization of indicators Z_{im}.

$$Z_{im}^{+}=\frac{z_{im}-min\left(z_{1m},z_{2m},\ldots,z_{30m}\right)}{max(z_{1m},z_{2m},\ldots,z_{30m})-min\left(z_{1m},z_{2m},\ldots,z_{30m}\right)} \tag{10}$$

$$Z_{im}^{-}=\frac{max(z_{1m},z_{2m},\ldots,z_{30m})-z_{im}}{max(z_{1m},z_{2m},\ldots,z_{30m})-min\left(z_{1m},z_{2m},\ldots,z_{30m}\right)} \tag{11}$$

In order to avoid the unbalanced distribution caused by excessive difference in index values, the data are standardized. In the above formula, Z_{im}^{+} and Z_{im}^{-} respectively refer to the positive and negative indicators after standardized processing, z_{im} represents the original value of indicator m of province i. m represents the five secondary indicators of digital infrastructure.

b The measure of information entropy E_m.

$$E_m=ln\frac{1}{n}\sum_{i=1}^{30}\left(\frac{Z_{im}}{\sum_{i=1}^{30}Z_{im}}\bullet ln\frac{Z_{im}}{\sum_{i=1}^{30}Z_{im}}\right) \tag{12}$$

Information entropy reflects the different information content of the same index, which can effectively avoid the influence of subjective factors in weight setting.

c Calculation of indicator weights P_m.

$$P_m=\frac{(1-E_m)}{\sum_{j=1}^{5}(1-E_m)} \tag{13}$$

According to the information entropy of each index, its weight is calculated.

d Calculation of the composite index *diginfra*.

$$diginfra=\sum\nolimits_{m=1}^{5}P_m\bullet Z_{im} \tag{14}$$

Based on the standardized value Z_{im} of each indicator and the weight P_m of each indicator, the multi-objective linear weighting function method is used to calculate the digital infrastructure level (*diginfra*) at the provincial level from 2012 to 2021.

④ Resource dependence (*dependence*). Resource dependence is gauged by the ratio of employment in the regional extractive industry to that in the manufacturing industry.

4.2.5. Control variables

In addition to energy digitalization, several internal and external factors can influence CP. Building upon existing research [116–118], we incorporate a series of control variables to account for these factors. These variables include ①Foreign direct investment (*fdi*). *fdi* can impact CP through pollution transition and knowledge spillover effects. We measure it using the proportion of foreign direct investment to GDP; ②Industrial enterprise size (*size*). The *size* of industrial enterprises is closely linked to their operational and production efficiency, potentially influencing CP. It is calculated as the share of industrial output value relative to the number of regional enterprises; ③Urbanization (*city*). The urbanization process often involves population migration, factor agglomeration, and urban infrastructure development, which can affect economic growth and environmental pollution. We use the percentage of the urban permanent population to quantify urbanization; ④Industrial structure (*ins*). The industrial layout and structure are crucial in determining the economic growth mode and can impact CP. We measure it as the ratio of tertiary industry output to secondary industry output; ⑤Transportation infrastructure (*trans*). *Trans* has a dual impact on CP.

On the one hand, it can enhance regional transportation conditions, facilitating the flow of resources and boosting low-carbon innovation and production efficiency. On the other hand, it may increase automobile exhaust emissions and fossil energy consumption. We estimate this variable using the ratio of total highway mileage to the total population.

In summary, the measurement and indicator sources of relevant variables in this paper are shown in Table 3.

4.3. Data source and descriptive statistics

We have selected 30 mainland Chinese provinces as the subjects of our study and collected panel data spanning from 2012 to 2021. Our data sources encompass regional CO_2 emissions data from CEADs (Carbon Emission Accounts & Datasets), which provide a more comprehensive view of regional carbon emissions by accounting for emissions from energy combustion and production processes, covering 47 economic sectors, the combustion of 17 fossil fuels, and cement production [119]. We have also gathered data on energy technology innovation from the Shanghai Intellectual Property (Patent) Public Service Platform, as outlined in Li et al. [72]. Non-fossil energy generation data were sourced from the China Electric Power Statistical Yearbook, while energy consumption data were compiled based on the China Energy Statistical Yearbook. Marketization index data were calculated and adjusted comparably using China's Marketization Index Report by Province (2021) [120]. Additionally, we included other data primarily obtained from the China Regional Economic Database and EPS global statistics. Furthermore, we have confirmed no multicollinearity issue among the variables, and specific descriptive information can be found in Table 4.

Fig. 3 presents geographical heat maps illustrating the mean regional values of low-carbon economy development and energy digitalization throughout the sample period. Darker colors indicate higher values. The distribution of regional low-carbon economy development exhibits noticeable spatial clustering rather than a uniform pattern. Provinces such as Beijing, Guangdong, Jiangsu, Fujian, Zhejiang, and Sichuan demonstrate relatively favorable low-carbon economic development, while Xinjiang, Qinghai, Gansu, Ningxia, and Inner Mongolia have lower values. Beijing's commendable performance in low-carbon economic development is noteworthy. In recent years, Beijing has consistently emphasized carbon governance through policy and technological advancements, achieving impressive results and establishing itself as a leading province in China's low-carbon economic development. Regarding regional energy digitalization, eastern China displays the darkest colors, indicating a high level of digitalization, while central China exhibits lighter colors. The eastern region's rapid digital industry growth, solid digital technology foundation, and advanced digital infrastructure contribute to its higher level of digitalization. In contrast,

Table 3
Variable declaration.

Type	Variable	Measurement	Source
Dependent variable	Carbon productivity (*cp*)	Malmquist-Luenberger productivity index	China Regional Statistical Yearbook China Energy Statistical Yearbook CEADS
Key independent variable	Energy digitalization (*enerdig*)	$enerdig_{it} = diginput_{it} \times digstrategy_{it}$	Departmental input-output table Corporate annual report
	Digital input in the energy industry (*diginput*)	Relative consumption coefficient	Provincial 42 departments input-output table (Published at the National Bureau of Statistics)
	Willingness of micro-entities for digital transformation (*digstrategy*)	Word frequency statistics based on natural language processing	M&A text in annual reports of listed energy companies (Reptile technique by Python)
Mechanism variables	Energy technology innovation (*enerinno*)	The number of patent applications for “non-fossil energy” and “energy conservation and emission reduction"	Shanghai Intellectual Property (patent) public service platform
	Energy structure optimization (*enerstru*)	The proportion of renewable energy generation	China Electric Power Statistical Yearbook
	Energy utilization efficiency (*enereffi*)	GDP/Energy consumption	China Regional Statistical Yearbook China Energy Statistical Yearbook
Threshold variables	Marketization (*market*)	Marketization index	Fan et al. [113]
	Environmental regulation (*regulation*)	Completed investment in industrial pollution control/ added value of secondary industry	China Regional Statistical Yearbook
	Digital infrastructure (*diginfra*)	Entropy method	China Electronic Information Industry Statistical Yearbook EPS global statistics
	Resource dependence (*dependence*)	Employment in extractive industries/employment in industry	EPS global statistics
Control variables	Foreign direct investment (*fdi*)	foreign direct investment/GDP	EPS global statistics
	Industrial enterprise size (*size*)	industrial output value/the number of regional enterprises	China Regional Economic Database
	Urbanization (*city*)	urban permanent population/total population	China Regional Economic Database
	Industrial structure (*ins*)	the tertiary industry output/the secondary industry output	China Regional Economic Database
	Transportation infrastructure (*trans*)	total highway mileage/total population	China Regional Economic Database

Table 4
The descriptive statistics of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
cp	300	0.853	0.235	0.578	2.549
enerdig	300	2.692	0.816	0.251	4.382
fdi	300	1.638	1.473	0.039	9.142
size	300	0.990	0.343	0.411	2.118
city	300	0.582	0.121	0.350	0.896
ins	300	1.218	0.691	0.518	5.169
trans	300	0.027	0.020	0.003	0.104

western regions, although not technologically advanced, face significant pressure regarding new energy distribution and power generation. This pressure drives the extensive integration of digital technology and new energy power generation, improving digitalization levels to some extent. Notably, Shanxi, a province rich in coal resources, demonstrates a low degree of digitalization. This observation underscores the challenges the fossil energy industry faces in achieving digitalization, which involves constraints related to technological progress and economic development that require careful consideration.

5. Empirical results and discussion

5.1. Results of direct effects

5.1.1. Baseline regression analysis

As shown in Table 5, the methods of POLS, RE, and FE are used in this study to estimate the low-carbon economy effects of ED. Among them,

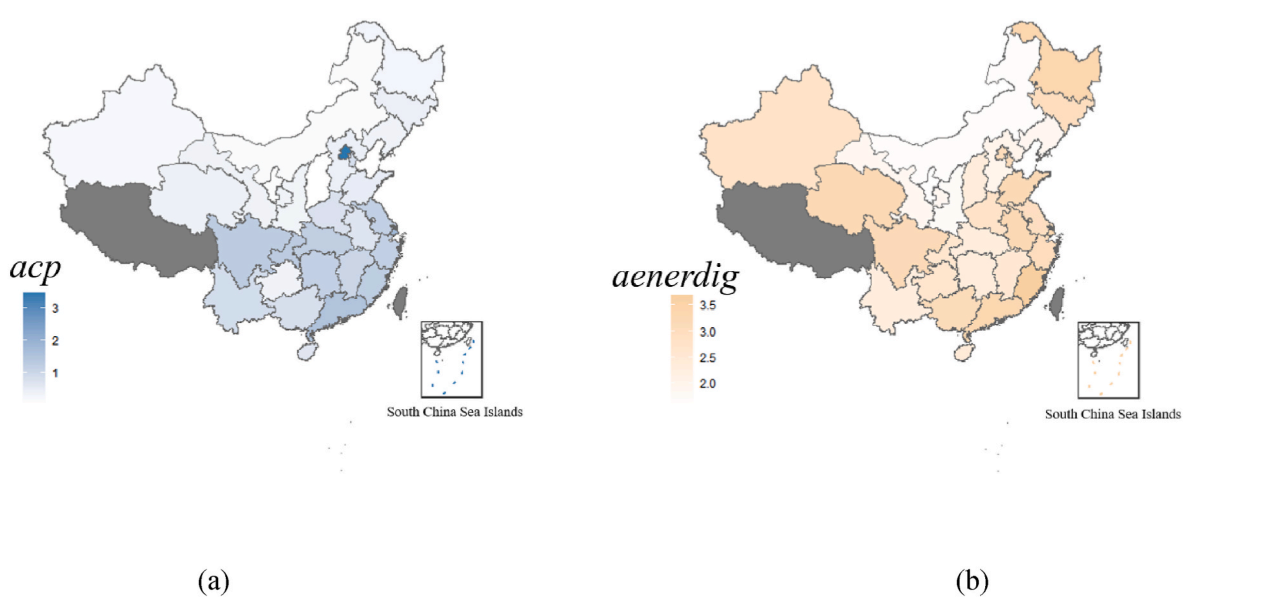

Fig. 3. Distribution maps of the *acp* (average value of CP) (a) and *aenerdig* (average value energy digitalization) (b).

columns (1), (3), and (5) only contain the core explanatory variable ED, while columns (2), (4), and (6) include all the control variables. All results show positive impact coefficients between core variables, validating hypothesis 1; that is, ED can promote the CP directly. Additionally, when control variables are included, the model's goodness of fit increases significantly, manifesting the rationality of variable screening. Further, according to the Hausman test, we will focus on the column (6). Regional CP will increase by 0.112 units for every ED unit increase. From a micro perspective, ED reconstructs the structure of traditional production factors and production links with data elements and triggers the intensive transformation of production mode, thus improving green productivity. From a meso perspective, ED reshapes the industrial organization forms through the networked platform and forms a widely interconnected ecological community, thus promoting the clean development of the energy industry. From a macro perspective, ED realizes carbon monitoring and feedback of all links of the energy value chain through integrating digital technology, operation technology, and electricity technology, thus boosting the economy's and society's intelligent and green development. Moreover, regarding variables, for every unit increase in the size of industrial enterprises, regional low-carbon economic development will increase by 0.768 units. Schumpeter's innovation theory [121] has emphasized that firm size is proportional to innovation. We suspect that although large enterprises will produce more pollution due to large-scale production, they have a greater advantage of low-carbon economic contribution supported by advanced technological innovations in emission reduction. The industrial structure can spur CP with a coefficient of 0.654, which is significant at the 5% level. Similar to Zhao et al.'s findings [122], the advanced development of industrial structure contributes to eliminating energy-intensive industries, optimizing the energy consumption structure, and stimulating green technology innovation, thereby promoting CP.

5.1.2. Endogenous analysis

Previous studies have suggested that low-carbon development can stimulate digitalization [92]. Therefore, it is essential to consider the possibility of reverse causality between ED and CP. Additionally, given the multitude of factors influencing CP, there may be missing variables, and the empirical results may be subject to unobservable factors. To address these concerns, we employ the instrumental variable method for model estimation.

We initiate the analysis by conducting the robust Durbin-Wu-Hausman (DWH) test to examine the endogeneity of the model. The test results yield a statistic value of 32.798, with a corresponding P-value of 0.000, indicating the presence of an endogeneity issue in the ED. We select two instrumental variables in light of two critical conditions for instrumental variables—correlation with endogenous variables but no correlation with random disturbance terms. ① The degree of topographic relief *iv*1 [43]: Regional topographic relief can impact the installation of digital equipment and the transmission of digital information, but it does not hadirectly affect CP. ② An interaction term between the number of post offices per million people in 1984 and the lag term of industrial robot installation density *iv*2 [123]: The number of post offices is historically linked to Internet penetration rates and communication technology development. However, with technological advancements, the role of post offices in modern society has diminished. By multiplying this variable by industrial robot installation density, we enhance its relevance to digitalization. It is important to note that the lag term of industrial robot installation density has a weak correlation with the current CP. The first two columns in Table 6 present the estimation results of the two-stage least squares (2SLS) method. According to the first-stage results, both *iv*1 and *iv*2 significantly enhance the level of ED, confirming their strong relationship with the endogenous variable. In the second-stage regression, the coefficient of *enerdig* is significantly positive, providing compelling evidence for hypothesis 1. Furthermore, the Cragg-Donald Wald statistic yields a value of 30.851, surpassing the 10% critical value of 19.930, affirming the effectiveness of instrumental variable selection.

Considering the serial correlations of CP, we introduce its lag term *L.cp* and apply GMM) to account for potential unobservable factors and minimize model estimation bias. The last two columns in Table 6 present the results of the system GMM model and the differential GMM. Both the AR and the Hansen test results validate the appropriateness of GMM. It is noteworthy that, even after addressing the endogeneity issue, ED continues to exhibit a significant positive impact on CP, reinforcing the robustness of our findings for hypothesis 1.

5.1.3. Heterogeneity analysis

(1) Analysis of regional heterogeneity

Based on the division of geographical regions in China, this study conducted a sub-sample heterogeneity test on four major regions of China. The results, presented in Table 7, indicate that only in the eastern and northeast regions does ED significantly impact CP. Notably, the low-carbon economic effect of ED is most pronounced in the eastern region, which aligns with the findings of Yi et al. [123]. This outcome can be attributed to the eastern region's more advanced digital technologies

Table 5
Results of baseline regression.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	POLS	POLS	RE	RE	FE	FE
enerdig	0.407***	0.106***	0.320***	0.104***	0.317***	0.112**
	(0.052)	(0.020)	(0.081)	(0.039)	(0.081)	(0.051)
fdi		0.138***		0.057		0.010
		(0.042)		(0.050)		(0.041)
size		−0.275***		0.571**		0.768**
		(0.033)		(0.258)		(0.282)
city		0.407**		0.616		1.086
		(0.161)		(1.429)		(1.460)
ins		0.698***		0.607**		0.654**
		(0.069)		(0.290)		(0.295)
trans		−0.134		−2.975		−14.160
		(0.594)		(6.282)		(11.070)
constant	−0.242	−0.470***	−0.001	−1.102***	−0.000	−1.265**
	(0.134)	(0.117)	(0.136)	(0.386)	(0.219)	(0.489)
N	300	300	300	300	300	300
R^2	0.204	0.666	0.349	0.612	0.349	0.630

Note: The significance levels of 0.10, 0.05, and 0.01 are represented by *, **, and ***, respectively. The statistics in parentheses refer to standard errors. The same as below.

Table 6
Results of instrumental variable regression and GMM regression.

Variable	(1)	(2)	(3)	(4)
	First stage of 2SLS	Second stage of 2SLS	System-GMM	Differential-GMM
enerdig		0.630***	0.015*	0.097***
		(0.111)	(0.008)	(0.035)
iv1	0.258**			
	(0.054)			
Iv2	0.173***			
	(0.036)			
L. CP			1.107***	0.736***
			(0.011)	(0.063)
constant	−0.787*	−1.483***	−0.044**	
	(0.426)	(0.291)	(0.018)	
Control variables	Yes	Yes	Yes	Yes
Time-fixed effect	control	control	control	control
Individual-fixed effect	control	control	control	control
P value of DWH test		0.000		
F value of Cragg-Donald Wald		30.851		
P value of Hansen test		0.100	0.879	0.515
P value of AR (1) test			0.009	0.003
P value of AR (2) test			0.734	0.265
N	300	300	270	240

and superior digital infrastructure conditions, which facilitate the demonstration of the low-carbon economic effect of ED. In contrast, despite having a higher carbon emission level due to coal burning, the northeast region experiences a more evident effect of ED on carbon reduction compared to the central and western regions. Given their current economic development and digital technology levels, this underscores the potential for high-energy consumption areas to contribute to carbon peak and carbon neutrality efforts.

(2) Analysis of time heterogeneity

Based on the division of geographical regions in China, this study conducted a sub-sample heterogeneity test on four major regions of China. The results, presented in Table 8, indicate that only in the eastern and northeast regions does ED significantly impact CP. Notably, the low-carbon economic effect of ED is most pronounced in the eastern region, which aligns with the findings of Yi et al. [123]. This outcome can be attributed to the eastern region's more advanced digital technologies and superior digital infrastructure conditions, which facilitate the demonstration of the low-carbon economic effect of ED. In contrast, despite having a higher carbon emission level due to coal burning, the northeast region experiences a more evident effect of ED on carbon reduction compared to the central and western regions. This underscores the potential for high-energy consumption areas to contribute to carbon peak and carbon neutrality efforts, given their current economic development and digital technology levels.

5.2. Results of indirect effects

Table 9 presents the intermediary mechanisms through which ED influences CP. Specifically, the first two columns employ a three-step regression, utilizing energy technology innovation (*enerinno*) as the intermediary variable. The results reveal that the impact coefficient of ED on energy technology innovation is 0.137, which not only passes the significance test with a p-value of 0.99 but also demonstrates statistical significance. Furthermore, the elasticity coefficient of energy technology innovation on CP is 0.263. Consequently, we can calculate that the indirect impact of ED on CP amounts to 0.036 (0.137 × 0.263), representing a substantial 32.171% of the total effect. Moving on to the middle two columns, we explore the results when energy structure optimization (*enerstru*) serves as the intermediary variable. Despite the critical coefficients in the stepwise regression being non-significant, it is vital to acknowledge the potential existence of a mediating effect, as emphasized by Wen and Ye [99]. To validate this, we conducted Sobel and Bootstrap tests, which yielded p-values of 0.000, indicating a partial mediating effect of clean energy structure transition. This effect amounts to 4.557% of the total impact. In the final set of columns (5) and (6), we present the results of a three-step regression with energy utilization efficiency (*enereff*) as the intermediary variable. These findings demonstrate that ED can indirectly influence CP through energy technology, energy structure, and energy utilization efficiency. This comprehensive support strongly validates hypothesis 2. In summary, our analysis indicates that ED has a dual impact: a direct effect on CP and multiple indirect effects mediated by crucial economic indicators. These findings underscore the complex nature of the relationship between ED and CP.

5.3. Results of threshold effects

Table 10 reveals the findings from the threshold effect analysis. Upon examining the p-values, it becomes evident that all four threshold variables exhibit a single threshold effect without encountering a situation of double thresholds. This observation further validates the first part of hypothesis 3 in this study. For a clearer perspective, when the marketization level, environmental regulation intensity, digital infrastructure

Table 7
Results of regional heterogeneity test.

Variable	(1)	(2)	(3)	(4)
	east	central	west	northeast
enerdig	0.261***	0.043	−0.038	0.034**
	(0.062)	(0.062)	(0.027)	(0.014)
fdi	−0.004	0.122	0.368***	−0.141***
	(0.033)	(0.084)	(0.075)	(0.042)
size	0.942***	0.532***	0.246***	−0.008
	(0.208)	(0.183)	(0.093)	(0.034)
city	−1.918	5.146***	0.343	3.737***
	(1.209)	(1.739)	(0.856)	(0.991)
ins	0.849***	0.356	0.443***	−0.061**
	(0.114)	(0.215)	(0.100)	(0.023)
trans	−17.600**	−35.850***	7.306	−0.373
	(7.620)	(10.080)	(11.690)	(3.401)
constant	0.432	−2.029***	−0.684**	−1.738***
	(0.649)	(0.512)	(0.330)	(0.562)
N	100	60	110	30
R^2	0.812	0.838	0.709	0.932

Table 8
Results of time heterogeneity test.

Variable	(1)	(2)
	2012–2015	2016–2021
enerdig	0.049**	0.078**
	(0.023)	(0.038)
fdi	0.002	0.168***
	(0.017)	(0.063)
size	0.385**	0.613***
	(0.165)	(0.104)
city	1.363	−1.175
	(0.936)	(0.933)
ins	0.711***	0.743***
	(0.214)	(0.081)
trans	8.846	−7.529
	(7.428)	(6.924)
constant	−1.491***	−0.225
	(0.430)	(0.396)
N	120	180
R^2	0.510	0.580

Table 9
Results of intermediary mechanism.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	enerinno	CP	enerstru	CP	enereffi	CP
enerdig	0.137***	0.076**	0.022**	0.107***	0.124***	0.043**
	(0.028)	(0.030)	(0.010)	(0.030)	(0.039)	(0.020)
fdi	−0.122***	0.042	0.005	0.009	−0.024	0.023
	(0.026)	(0.027)	(0.009)	(0.027)	(0.036)	(0.018)
size	0.079	0.748***	−0.062**	0.783***	0.919***	0.258***
	(0.083)	(0.083)	(0.028)	(0.086)	(0.113)	(0.065)
city	13.150***	−2.368**	−0.771***	1.265**	5.178***	−1.793***
	(0.588)	(1.001)	(0.197)	(0.624)	(0.803)	(0.444)
ins	0.810***	0.442***	−0.058***	0.668***	0.455***	0.402***
	(0.061)	(0.079)	(0.021)	(0.064)	(0.084)	(0.045)
trans	19.150***	−19.190***	−1.342	−13.850***	−1.723	−13.200***
	(4.924)	(5.063)	(1.652)	(5.084)	(6.717)	(3.454)
enerinno		0.263***				
		(0.062)				
enerstru				0.232		
				(0.189)		
enereffi						0.556***
						(0.032)
constant	2.687***	−1.971***	1.281***	−1.562***	−3.020***	0.414*
	(0.269)	(0.315)	(0.090)	(0.368)	(0.367)	(0.211)
Sobel test	Z = 3.600		Z = 3.341		Z = 5.562	
	P = 0.000		P = 0.001		P = 0.000	
Bootstrap test1	Z = 3.490		Z = 3.600		Z = 4.84	
	P = 0.000		P = 0.000		P = 0.000	
N	300	300	300	300	300	300
R^2	0.941	0.654	0.252	0.632	0.657	0.830

condition, and resource dependence reach 9.2225, 0.0006, 0.4377, and 0.0556, respectively, the likelihood ratio (LR) value of the statistical test becomes zero, as depicted in Fig. 4.

Table 11 presents the results of the threshold regression analysis. Specifically, ① Column (1) reports the threshold effect results based on marketization (*market*) as the adjusting variable. When the marketization level exceeds 9.2225, the influence coefficient changes from 0.083 to 1.181, with statistical significance at the 1% level. This aligns with Liang et al.'s findings [124], suggesting that digitalization has a more favorable impact in regions with higher levels of marketization. Chen [79] also noted that mature markets can enhance the role of digitalization in promoting renewable energy development, contributing positively to low CP. A mature market system provides institutional support for digitalization dividends, aiding resource allocation and low-carbon innovation, ultimately yielding a more significant low-carbon economic effect. ② Column (2) presents the regression results with environmental regulation (*regulation*) as the threshold variable. When environmental regulations become more stringent, the coefficient of the core explanatory variable decreases by 55.072%. This differs from the perspective of Yang and Liang [125] and supports the "compliance cost theory" of environmental regulation. Excessive command-based environmental regulations can impose innovation costs on enterprises [126] and hinder the digitalization process, limiting the contribution of ED to low-carbon economic development. Therefore, the government should consider adopting a market-oriented and government-coordinated approach to balance pollution control investment and digitalization promotion. ③ Column (3) reports the nonlinear relationship when adjusting for digital infrastructure (*diginfra*). The result shows that when *diginfra* exceeds 0.4377, a 1% increase in ED leads to a 0.205% increase in CP. This finding is consistent with Chen's [92] observation that advanced digital infrastructure is the cornerstone of digitalization, providing robust technical support for fully releasing the low-carbon economic impact. ④ Column (4) presents regression results with resource dependence (*dependence*) as the threshold variable. When resource *dependence* is less than 0.0556, the influence coefficient of ED on CP is 0.176, significant at the 0.01 level. However, the effect coefficient is no longer statistically significant when dependence surpasses the threshold value. The paper suggests that regions with high resource dependence tend to adopt a rigid and extensive development approach, squeezing high-end factors such as technology and human capital. This limits the carbon reduction impact of ED in these regions.

5.4. Results of spatial effects

5.4.1. Analysis of spatial correlation

This study uses the Moran index to conduct a spatial correlation test. Table 12 displays the global Moran index based on the economic geographic distance weight matrix. Both low-carbon economic development and ED exhibit a significant positive spatial correlation. However, it is worth noting that the Moran index varies, suggesting that

Table 10
Results of threshold effect test.

Threshold variable (Threshold value)	Threshold test	F value	P value	BS times	Critical value		
					10%	5%	1%
market	Single threshold	36.440	0.047	300	29.197	36.310	60.478
(9.2225)	Double threshold	20.790	0.243	300	31.443	38.932	56.379
regulation	Single threshold	26.820	0.023	300	19.225	23.293	30.974
(0.0006)	Double threshold	4.200	0.740	300	19.797	25.767	33.617
diginfra	Single threshold	69.820	0.000	300	24.355	31.430	52.964
(0.4377)	Double threshold	11.960	0.343	300	23.523	34.887	54.510
dependence	Single threshold	109.680	0.003	300	40.142	51.981	98.846
(0.0556)	Double threshold	16.860	0.487	300	40.354	57.820	78.173

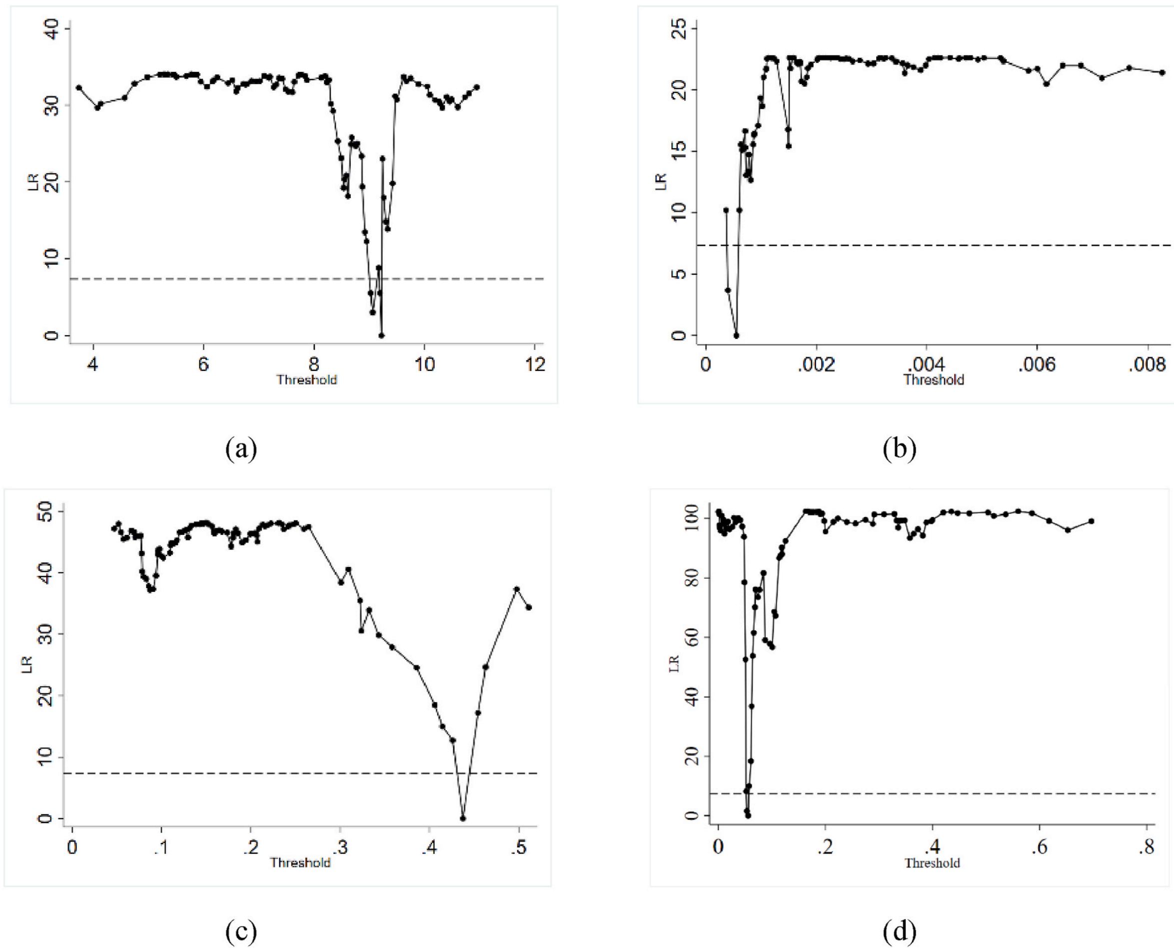

Fig. 4. Likelihood ratio function graph of the threshold variables: market (a), regulation (b), diginfra (c), and dependence(d).

spatial distribution patterns substantially influence both variables. Fig. 5 illustrates that most data points are clustered in the first and third quadrants, indicating a “high-high” aggregation pattern and “low-low” aggregation for both variables.

Furthermore, we applied the spatial Markov chain model to investigate the spatio-temporal correlation of regional CP. This analysis categorized CP into three types: 1, 2, and 3, representing low, medium, and high CP, respectively. Table 13 presents the transition probability matrix for both traditional and spatial Markov models. Under the traditional Markov analysis, the following observations can be made: ① The diagonal probability is greater than the non-diagonal values, exceeding 75%, indicating strong stability in regional carbon performance during the study period. In contrast, the non-diagonal probability values are smaller, with the highest value at 15.493%. This suggests that the spatial transfer of carbon performance is a gradual process that requires coordinated efforts in terms of technology and policy. ② The probability values at the two diagonal corners are 94.203% and 98.361%, significantly higher than the 84.507% in the middle of the matrix. This pattern indicates a “Matthew effect” in the distribution of CP over successive years. ③ By comparing the mean of non-diagonal probabilities, it is evident that the probability of downward transfer in interregional CP (1.639%) is significantly lower than the probability of upward transfer (10.645%). This signifies a positive trend in China’s low-carbon transformation.

Notable changes in probability values are observed upon comparing the spatial Markov chain with the traditional Markov chain, underscoring the critical role of neighborhood states in CP. The statistical test shows $df = 3\times(3-1)^2 = 12$, $\alpha = 0.005$, $Q_b = 33.562 > \chi^2(12) = 28.300$. This result rejects the null hypothesis that regional CP types are independent. Therefore, we conclude that regional CP types exhibit significant spatial correlation with neighboring states. ① Neighborhood State Analysis: When the neighborhood state is categorized as type 3, the probability of regional carbon performance transfer is the highest (11.111%) and lowest (4.061%) when the neighborhood is classified as type 1. This suggests that regional CP exhibits spatial correlation, with low-carbon neighborhoods more likely to contribute to “carbon improvement” within the region, while high-carbon neighborhoods tend to have a “carbon locking” effect. ② Initial State Analysis: For initial states 1, 2, and 3, the average probability of regions maintaining their original carbon performance type is 88.437%, 86.917%, and 98.889%, respectively. Compared to the traditional Markov analysis, regions with an initial state of type 1 experience a noticeable decrease of 5.766%. This indicates that regions with high CP display less volatility in low-carbon development than other regions. ③ Transition Probability Analysis: On one hand, as the neighborhood state transitions from 1 to 3, the upward transfer probability of regional states gradually increases, while the downward transfer probability gradually decreases, exhibiting a “club convergence” phenomenon. On the other hand, when the neighborhood is type 1, the probability of the initial region maintaining the same CP type is 96.907%, and when the neighborhood is type 3, the probability is 1. These values are higher than those observed in the traditional Markov analysis (94.203% and 98.361%). This reinforces the “Matthew effect.” ④ Analysis of the Number of Regions: When the neighborhood state is 3, 24 regions (nearly 50%) exhibit low-carbon characteristics during the period t. Conversely, when the neighborhood state is 1, high-carbon regions account for 84.348%. In both cases, the number of regions with the same CP type exceeds 50%, indicating a collaborative pattern in regional CP levels.

Table 11
Result of the threshold model.

Variable	(1) market	(2) regulation	(3) diginfra	(4) dependence
enerdig (*market* ≤ 9.2225)	0.083***			
	(0.028)			
enerdig (*market* > 9.2225)	0.181***			
	(0.030)			
enerdig (*regulation* ≤ 0.0006)		0.207***		
		(0.034)		
enerdig (*regulation* > 0.0006)		0.093***		
		(0.028)		
enerdig (*diginfra* ≤ 0.4377)			0.079***	
			(0.027)	
enerdig (*diginfra* > 0.4377)			0.205***	
			(0.029)	
enerdig (*dependence* ≤ 0.0556)				0.176***
				(0.026)
enerdig (*dependence* > 0.0556)				0.012
				(0.027)
fdi	0.010	−0.013	0.043*	−0.023
	(0.025)	(0.026)	(0.025)	(0.023)
size	0.672***	0.731***	0.597***	0.567***
	(0.082)	(0.082)	(0.080)	(0.076)
city	1.066*	1.036*	0.750	0.808
	(0.573)	(0.582)	(0.547)	(0.519)
ins	0.617***	0.629***	0.621***	0.606***
	(0.060)	(0.061)	(0.057)	(0.054)
trans	−16.700***	−13.400***	−13.810***	−10.650**
	(4.812)	(4.874)	(4.561)	(4.352)
constant	−1.052***	−1.114***	−0.875***	−0.767***
	(0.264)	(0.268)	(0.254)	(0.242)
N	300	300	300	300
R^2	0.672	0.661	0.703	0.732

5.4.2. Analysis of spatial effects

Based on a series of statistical tests, including LM, Wald test, LR, and Hausman, we have established the SDM, with the results presented in Table 14. The coefficients of ρ in the three fixed effects SDMs are significantly positive, providing further evidence of the spatial correlation of CP. Given the significance of the variables and the LR test results [127], our focus will be on the outcomes of the double fixed-effect SDM, as illustrated in column (3). In this model, it is evident that ED positively impacts CP, with a coefficient of 0.200 for $W \times enerdig$. This finding indicates that ED possesses spillover effects on neighboring regions, thereby offering preliminary support for hypothesis 4 outlined in this paper.

It is important to note that due to the spatial rebound effect among variables, fully capturing the spatial correlation requires examining the influence of variables and their spatial interaction terms and considering various spatial influences of ED. To achieve this, we have applied the dynamic SDM, and the results are presented in Table 15. ① Regarding the spatial direct effect, ED significantly and positively impacts regional CP. Importantly, there is no significant change in the short and long-term direct effects. Specifically, for every 1% increase in ED, the CP of the internal region increases by 0.066% during the short period and 0.051% in the long run. ② Concerning the spatial spillover effect, ED demonstrates a favorable spillover effect on the CP of external regions, providing strong evidence supporting hypothesis 4 outlined in this paper. This spillover effect is more pronounced during the short period, with elastic coefficients of 0.232 and 0.188, respectively. The possible reason for this is that it is easier to establish collaborative digital strategies between regions in the long run, which may weaken the spillover effect caused by peer effects and, consequently, reduce the long-term spatial spillover effect. ③ Regarding the spatial total effect, it shows a significant positive impact in both the long and short term due to the accumulation of positive direct and spillover spatial effects.

5.5. Robustness test

In terms of robustness testing, this study conducts four different estimations to assess the robustness of the results. The outcomes of these tests are presented in Table 16. The four robustness tests involve replacing the core independent variable, substituting the dependent variable, reducing the sample period, and addressing extreme values. The results are as follows: ① Replace the core independent variable. In column (1), the core independent variable ED is replaced by the proportion of intangible assets in energy enterprises (*digreplace*), which can serve as a proxy for the digitalization degree of enterprises. The results demonstrate that the proportion of intangible assets in energy enterprises is positively associated with CP, reaffirming the reliability of the previous conclusions.; ② Replace the dependent variable. In column (2), per capita carbon emissions are introduced as a reverse substitute variable for low-carbon economic development, following Guo et al. [43]. The analysis reveals that ED effectively reduces per capita carbon emissions, further supporting the earlier findings: ③ Reduce sample period. Column (3) presents the estimation results after excluding the initial and final periods of the research sample, retaining data from 2013 to 2020. The coefficients and significance levels of the variables remain consistent with the previous findings, demonstrating the robustness of the results over this reduced sample period; ④ Eliminate the extreme value. Inspired by Luo et al. [47], 5% extreme values for all variables are removed to mitigate the influence of outliers. This approach enhances the credibility of the findings, as shown in column (4).

5.6. Discussion

This study seeks to investigate the multifaceted effects of energy digitalization on CP. The objective is to furnish empirical evidence and policy guidance for transforming a digitally-driven energy system, underscoring its potential for low-carbon development.

On the one hand, paralleling the research paradigms in extant literature [47,96], the multidimensional impact of digitalization on low-carbon development has been comprehensively examined.

Table 12
Results of Moran's I.

Year	*CP* I	Z	E(I)	sd(I)	Year	*enerdig* I	Z	E(I)	sd(I)
2011–2012	0.174**	2.239	−0.034	0.093	2012	0.039	0.605	−0.034	0.121
2012–2013	0.167**	2.151	−0.034	0.094	2013	0.126*	1.308	−0.034	0.123
2013–2014	0.139**	1.908	−0.034	0.091	2014	0.107	1.138	−0.034	0.124
2014–2015	0.16**	2.102	−0.034	0.092	2015	0.256***	2.357	−0.034	0.123
2015–2016	0.15**	2.037	−0.034	0.091	2016	0.350***	3.163	−0.034	0.122
2016–2017	0.144**	2.05	−0.034	0.087	2017	0.213**	1.99	−0.034	0.124
2017–2018	0.141**	2.065	−0.034	0.085	2018	0.212**	1.977	−0.034	0.125
2018–2019	0.132**	1.966	−0.034	0.085	2019	0.277***	2.517	−0.034	0.124
2019–2020	0.116**	1.797	−0.034	0.084	2020	0.217**	2.029	−0.034	0.124
2020–2021	0.125**	1.900	−0.034	0.084	2021	0.150*	1.522	−0.034	0.121

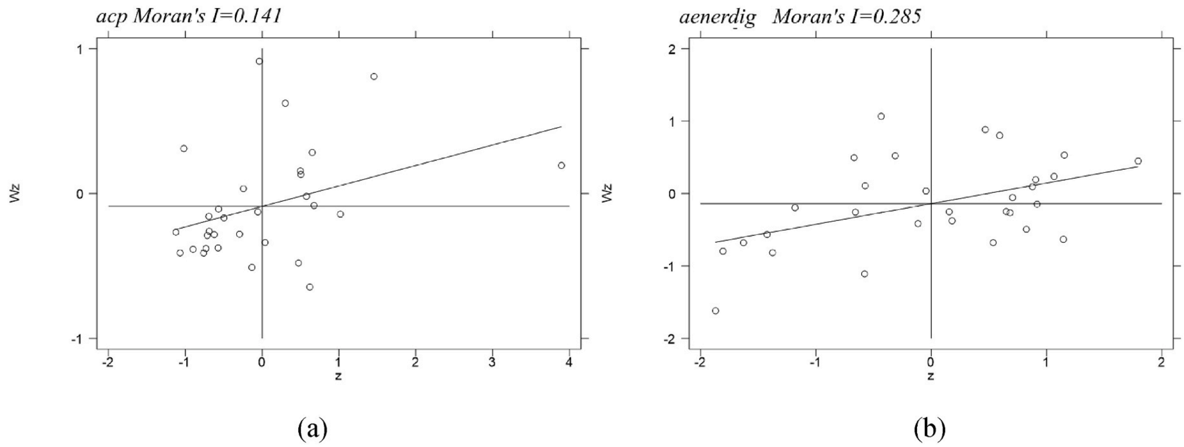

Fig. 5. Moran scatter plots of *acp* (the mean value of *CP)* (a) and *aenerdig* (the mean value *enerdig)* (b).

Table 13
Results of spatial Markov model.

Markov Type	Neighborhood Type	t\t+1	1	2	3	n
Traditional Markov	\	1	0.942	0.058	0.000	138
		2	0.000	0.845	0.155	71
		3	0.000	0.016	0.984	61
Spatial Markov	1	1	0.969	0.031	0.000	97
		2	0.000	0.909	0.091	11
		3	0.000	0.000	1.000	7
	2	1	0.906	0.094	0.000	32
		2	0.000	0.810	0.190	42
		3	0.000	0.033	0.967	30
	3	1	0.778	0.222	0.000	9
		2	0.000	0.889	0.111	18
		3	0.000	0.000	1.000	24

Table 14
Results SDM model regression.

Variable	(1)	(2)	(3)
	ind	time	both
enerdig	0.083***	0.084**	0.093***
	(0.021)	(0.036)	(0.021)
fdi	0.058***	0.092***	0.046**
	(0.019)	(0.021)	(0.019)
size	0.204***	−0.279***	0.143**
	(0.064)	(0.079)	(0.067)
city	−3.271***	−2.135***	−3.659***
	(0.970)	(0.573)	(0.973)
ins	0.577***	0.767***	0.544***
	(0.066)	(0.045)	(0.070)
trans	1.550***	1.721***	1.630***
	(0.102)	(0.180)	(0.104)
W×enerdig	0.138***	0.045	0.200***
	(0.040)	(0.088)	(0.052)
W×fdi	0.095*	0.222***	−0.037
	(0.049)	(0.086)	(0.064)
W×size	0.072	0.764***	−0.277
	(0.129)	(0.230)	(0.192)
W×city	−18.160***	−2.299	−20.400***
	(2.230)	(1.944)	(2.516)
W×ins	0.391***	−0.223	0.331
	(0.144)	(0.180)	(0.234)
W×trans	1.727***	−1.362***	2.417***
	(0.306)	(0.440)	(0.361)
ρ	−0.347***	0.201**	−0.453***
	(0.105)	(0.098)	(0.106)
σ^2	0.018***	0.121***	0.017***
	(0.002)	(0.010)	(0.001)
N	300	300	300
Log-Likelihood	172.498	−109.645	182.333
LR-ind	19.670**		
LR-time	583.960***		

Empirical results based on microscopic data validate digitalization's low-carbon potential and regional heterogeneity's impact [95]. Concurrently, our findings suggest that energy technology innovation acts as a positive transmission mechanism, furnishing robust evidence for its current intermediary role in technology innovation [62]. Additionally, our analysis reveals that CP exhibits spatial correlation characteristics. Through spatial transmission, digitalization can exert a positive spatial influence on regional external CP levels, consistent with the study [128], laying a theoretical foundation for further exploration of digitalization's spatial effects.

On the other hand, our research has yielded several unexpected insights and novel contributions. Firstly, this represents the inaugural quantitative investigation into the digitalization of the energy sector, augmenting the body of theoretical research on industrial digitalization, building upon previous studies focused on overall industrial [50], manufacturing sector digitalization [129] and agriculture [130]. Notably, our study does not corroborate the inverted U-shaped relationship between energy digitalization and CP, diverging from the findings of previous studies of Zhao et al. [104] and Cheng et al. [55]. This could be attributed to the dual considerations of carbon emissions and economic benefits, where energy digitalization potentially restructures factor compositions and deepens industrial organization forms, propelling the low-carbon transition of the industry and serving as a pivotal point for economies to surpass the Environmental Kuznets Curve (EKC) inflection point. Secondly, the mediating regression results validate the positive transmission mechanism of energy structure and energy utilization efficiency, thereby enriching the mechanism research on digital carbon reduction and offering new directions for governmental policy formulation. Thirdly, building upon existing studies on the regulatory roles of marketization [52] and environmental regulation [93], our research further probes the heterogeneity in external infrastructure and energy dependence in digitalization, addressing the current research gap on the nonlinear relationship between digitalization and low-carbon development. This provides theoretical underpinnings for the formulation of region-specific energy digitalization policy. Lastly, the spatial Markov chain analysis reveals the presence of "Matthew effect" and "club-driven" phenomena in the spatio-temporal distribution of China's regional CP. This enriches the understanding of CP's spatial and temporal distribution characteristics, extending beyond the spatial correlations established by the Moran index [47,55]. It is noteworthy that the short-term spatial impact of energy digitalization is more pronounced compared to long-term spatial effects. This finding supplements existing research on the spatial implications of

Table 15
The decomposition of spatial effect.

Variable	Short-term spatial effects			Long-term spatial effects		
	Direct	Spillover	Total	Direct	Spillover	Total
enerdig	0.066***	0.232***	0.298***	0.051**	0.188***	0.238***
	(0.022)	(0.051)	(0.058)	(0.024)	(0.042)	(0.044)
Control variables	Control					
ρ	0.220*					
	(0.132)					
σ^2	0.016***					
	(0.001)					
Log- Likelihood	−4404.537					

Table 16
Results of the robustness test.

Variable	(1)	(2)	(3)	(4)
	X. replace	Y. replace	Timecut	Winsor
digreplace	25.720*			
	(15.140)			
enerdig		−0.034***	0.109***	0.119***
		(0.007)	(0.032)	(0.029)
fdi	0.016	−0.014***	0.034	0.008
	(0.027)	(0.004)	(0.035)	(0.026)
size	0.760***	0.093***	0.632***	0.753***
	(0.088)	(0.015)	(0.093)	(0.084)
city	0.912	0.305***	0.515	1.218**
	(0.668)	(0.075)	(0.763)	(0.606)
ins	0.721***	−0.050***	0.625***	0.619***
	(0.062)	(0.009)	(0.072)	(0.063)
trans	−8.800*	−0.420	−11.700**	−14.230***
	(5.151)	(0.383)	(5.774)	(5.138)
constant	−1.150***	0.017	−0.856**	−1.300***
	(0.310)	(0.036)	(0.345)	(0.274)
N	300	300	240	300
R^2	0.614	0.586	0.590	0.632

digitalization and offers significant theoretical contributions to the strategies for inter-regional digital transformation collaboration.

6. Conclusion and implications

6.1. Conclusions

The energy sector is undergoing a transformative phase marked by a burgeoning digital technology revolution and industrial metamorphosis, establishing a robust impetus for low-carbon development. Utilizing provincial data from China spanning 2012 to 2021, this study strives to unravel the intricate interplay between ED and developing a low-carbon economy through theoretical analysis and empirical testing. Our findings culminate in four pivotal insights: ① Energy digitalization markedly enhances CP, a valid conclusion even after conducting endogeneity and robustness assessments. Additionally, heterogeneity analyses reveal that this positive effect is more pronounced in China's eastern regions and the years after 2015. ② Energy digitalization indirectly influences CP by innovating energy technology, refining the clean energy structure, and boosting energy utilization efficiency. Notably, improvements in energy utilization efficiency emerge as the most influential factor. ③ The relationship between ED and CP is nonlinear and is influenced by external environmental factors. The existence of mature markets, suitable environmental regulations, advanced digital infrastructure, and reduced dependence on resources tend to foster a more favorable environment for this relationship. ④ Both ED and CP exhibit distinct spatial aggregation characteristics. Energy digitalization not only bolsters CP within its region but also generates positive spillover effects on CP in neighboring regions, with these influences being more significant in the short term.

6.2. Policy implications

Given the above findings, we propose policy implications from three levels.

On a national level, there is an urgent need to advance the strategy of ED, accelerate the digitalization of energy sectors, and construct new power systems characterized by digitalization to drive the clean and intelligent development of energy systems. Firstly, it is essential to bolster digital infrastructure construction within the energy industry, providing the necessary hardware support for ED. This entails implementing specific actions in critical areas such as intelligent manufacturing, the energy Internet, smart grids, and energy big data. Secondly, guided by the "dual carbon" goal, it is necessary to promote integration innovation of digital and energy technology. This includes fostering the rapid development of digitalization in areas such as energy conservation, environmental protection, new energy, energy storage, distributed energy, and more. These efforts will enhance the development quality and efficiency of the energy industry. Macro-level strategies can be explored in constructing renewable energy power stations supported by data and processes, optimizing carbon emission management in conventional power supply through digital means, and enhancing the intelligent optimization of multi-level power system operations that support renewable energy.

At the regional level, governments should focus on institutional development to create a supportive regulatory environment for ED. Regional governments should establish an inclusive, differentiated, and precise policy framework based on environmental regulation intensity, market competition levels, digital infrastructure construction, and carbon emission reduction goals. Instead of excessive government intervention, the emphasis should be on promoting market-oriented reforms, reducing direct resource allocation, and avoiding administrative monopolies to foster a conducive institutional environment for ED. Furthermore, considering the spatial effects of ED on CP, inter-regional governments should collaborate in building digital networks to harness the regional benefits of digitalization effectively. Breaking down digital barriers, establishing inter-regional energy networks, and highlighting the relative strengths of different zones, especially between the eastern and northeastern regions, is essential. Given the disparities in digital infrastructure and resource endowments between the eastern and central regions, the central and western regions may require additional support to realize the full potential of digital transformation's carbon emission reduction. Leveraging the financial and technological advantages of the eastern region while optimizing renewable energy infrastructure in the central and western regions can enhance the adoption of clean energy.

At the enterprise level, energy companies, as key players in ED, must proactively respond to the inevitable digital transformation trend. Enterprises should actively engage in industry-university-research collaboration strategies, strengthen partnerships with universities and energy research institutes, enhance digital literacy, and bolster digital innovation capabilities. There is a pressing need to invest in research and development, focusing on applying digital technology throughout the energy supply chain, for instance, encouraging innovation in smart grid and multi-energy complementary technology for transmission and fostering the development of virtual power plants and electric energy substitution technology for distribution. Enterprises should also focus on innovation in energy data and deepen its application. This includes breakthroughs in critical technologies like resource scheduling, monitoring management, in-depth analysis, and the integration of cutting-edge technologies such as the Internet of Things, artificial intelligence, blockchain, big data, edge computing, and digital twins with core business processes. Additionally, energy companies should adapt their digital strategies, improve their organizational structures and operational mechanisms, and facilitate the seamless integration of digital technologies with business strategies and objectives. Developing a diverse talent pool for ED is crucial. Encouraging employees to enhance their proficiency in applying digital technology achievements and fostering technical exchanges and cooperation are essential steps to realize ED's low-carbon development benefits fully.

6.3. Limitations and future directions

We have delved deep into the impact of digital transformation on CP, but it is important to acknowledge certain limitations in our study. Firstly, the absence of authoritative data on the energy industry and the exclusion of data on unlisted companies might limit the applicability of our findings, especially in comparison to developed economies. Secondly, given the complexity of the issue and the rigorous mathematical relationships involved, addressing endogeneity in the mediating effect could have been addressed more effectively. Endogeneity is a well-recognized challenge in econometrics. Lastly, the lexicon of digital transformation constructed in this article may require periodic updates in future research due to the rapid evolution of the digital economy.

In future studies, the research framework developed in this paper can be extended to different industries, such as the cultural industry, agriculture, tourism, or other developing countries. This expansion will further enrich our understanding of the relationship between digital transformation and CP in diverse contexts. To mitigate the endogeneity issues in econometric models, a promising approach involves combining theoretical analysis and mathematical derivation to establish a robust mathematical model between the core variables. Additionally, to keep the research up-to-date, it is advisable to regularly update the keyword analysis by capturing critical terms from policy texts related to digital transformation and industrial development planning each year. This will allow for the continuous expansion of the digital transformation vocabulary in future studies.

Ethics approval

Not applicable.

Consent for participate

Not applicable.

Consent for publication

Not applicable.

Conflict for publication

Not applicable.

Funding

This work was supported by the National Social Science Fund of China (23CGL041).

Availability of data and materials

Data is available on reasonable requirements.

Credit author statement

Conceptualization: [Shi Ziyi]; Methodology: [Shi Ziyi, Lawrence Loh]; Software: [Shi Ziyi, Han Dongri]; Data Curation: [Shi Ziyi, Lawrence Loh]; Writing- original draft: [Shi Ziyi, Lawrence Loh]; Writing-review and editing: [Shi Ziyi]; Supervision: [Shi Ziyi, Lawrence Loh]; Visualization: [Shi Ziyi, Han Dongri]; Revise: [Shi Ziyi, Wu Hongshuang]

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

We are very grateful to the editors and anonymous reviewers for reviewing this paper.

References

[1] S.Y. Ren, Y. Hao, L. Xu, H.T. Wu, N. Ba, Digitalization and energy: how does internet development affect China's energy consumption? Energy Econ. 98 (2021) 105220.
[2] M. Murshed, N. Apergis, M.S. Alam, U. Khan, S. Mahmud, The impacts of renewable energy, financial inclusivity, globalization, economic growth, and urbanization on carbon productivity: evidence from net moderation and mediation effects of energy efficiency gains, Renew. Energy 196 (2022) 824–838.
[3] G.C. Fang, Z.Y. Gao, C.W. Sun, How the new energy industry contributes to carbon reduction? -Evidence from China, J. Environ. Manag. 329 (2023) 117066.
[4] X.G. Zhao, L. Xu, Y. Zhou, How to promote the effective implementation of China's Renewable Portfolio Standards considering non-neutral technology? Energy 238B (2022) 121748.
[5] Z. Jan, F. Ahamed, W. Mayer, N. Patel, G. Grossmann, M. Stumptner, A. Kuusk, How to promote the effective implementation of China's Renewable Portfolio Standards considering non-neutral technology? Expect Systems With Applications 216 (2023) 119456.
[6] Q. Wu, Digital transformation of energy enterprises: the role of the "sixth energy" is highlighted, Energy 1 (2022) 36–39.
[7] M. Shahbaz, J.D. Wang, K.Y. Dong, J. Zhao, The impact of digital economy on energy transition across the globe: the mediating role of government governance, Renewable Sustainable Energy Rev. 166 (2022) 112620.
[8] Y. Lyu, Y. Wu, G. Wu, W.Q. Wang, et al., Digitalization and energy: how could digital economy eliminate energy poverty in China? Environ. Impact Assess. Rev. 103 (2023) 107243.
[9] L. Ha, Are digital business and digital public services a driver for better energy security? Evidence from a European sample, Environ. Sci. Pollut. Control Ser. 29 (18) (2023) 27232–27256.
[10] D.H. Husaini, H.H. Lean, Digitalization and energy sustainability in ASEAN, Resour. Conserv. Recycl. 184 (2022) 106377.
[11] Q. Xu, M.R. Zhong, X. Li, How does digitalization affect energy? International evidence, Energy Econ. 107 (2022) 105879.
[12] K.H. Choi, G.H. Kwon, A study on the strategy of digital technology utilization in energy sector's new industries: from the perspective of technology convergence patterns, innovation effects and prediction, Journal of Korea Technology Innovation Society 24 (2) (2021) 1–21.
[13] H.Y. Zhang, S.Z. Gao, P. Zhou, Role of digitalization in energy storage technological innovation: evidence from China, Renewable Sustainable Energy Rev. 171 (2022) 113014.
[14] K. Li, X.B. Cao, Research on the formation mechanism of digital resilience capability of energy enterprises, Energy of China 43 (7) (2021) 73–80.
[15] R.J. Zheng, G. Wu, Y. Cheng, H.M. Liu, How does digitalization drive carbon emissions? The inverted U-shaped effect in China, Environ. Impact Assess. Rev. 102 (2023) 107203.
[16] C. Ancillai, A. Sabatini, M. Gatti, A. Perna, Digital technology and business model innovation: a systematic literature review and future research agenda, Technol. Forecast. Soc. Change 188 (2023) 122307.

[17] X. Li, T. Wu, H.J. Zhang, D.Y. Yang, Digital technology adoption and sustainable development performance of strategic emerging industries: the mediating role of digital technology capability and the moderating role of digital strategy, Journal of Organizational And User Computing 34 (8) (2023) 315645.
[18] G.H. Zhou, C. Zhang, Z. Li, K. Ding, C. Wang, Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing, Int. J. Prod. Res. 58 (4) (2020) 1034–1051.
[19] M. Kohtamaki, V. Parida, P. Oghazi, H. Gebauer, T. Baines, Digital servitization business models in ecosystems: a theory of the firm, J. Bus. Res. 104 (2019) 380–392.
[20] T. He, M.J. Liu, C.W. Phang, J. Luo, Toward social enterprise sustainability: the role of digital hybridity, Technol. Forecast. Soc. Change 175 (2021) 121360.
[21] F. Donati, S.M.R. Dente, C. Li, X. Vilaysouk, A. Froemelt, et al., The future of artificial intelligence in the context of industrial ecology, J. Ind. Ecol. 26 (4) (2022) 1175–1181.
[22] S.C. Liu, J.C. Tan, S.X. Zhang, H.C. Lin, Can corporate digital transformation promote input-output efficiency? Journal of Management World 37 (5) (2021) 170–190+13.
[23] C. Gaglio, E. Kraemer-Mbula, E. Lorenz, The effects of digital transformation on innovation and productivity: firm-level evidence of South African manufacturing micro and small enterprises, Technol. Forecast. Soc. Change 182 (2022) 121785.
[24] N. Li, X.H. Wang, Z.R. Wang, X.Y. Luan, The impact of digital transformation on corporate total factor productivity, Front. Psychol. 13 (2022) 1071986.
[25] J. Torrent-Sellens, A. Diaz-Chao, A.P. Miro-Perez, J. Sainz, Towards the Tyrell corporation? Digitisation, firm-size and productivity divergence in Spain, Journal of Innovation & Knowledge 7 (2) (2022) 100185.
[26] H.Y. Deng, G. Bai, Z.Y. Shen, Digital economy and its spatial effect on green productivity gains in manufacturing: evidence from China, J. Clean. Prod. 378 (2022) 134539.
[27] W.R. Pan, T. Xie, Z.W. Wang, L.S. Ma, Digital economy: an innovation driver for total factor productivity, J. Bus. Res. 139 (2022) 303–311.
[28] X.H. Ren, G.D. Zeng, G. Gozogor, How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities, J. Environ. Manag. 330 (2023) 117125.
[29] K.Z. Dai, Z. Huang, S.M. Wang, Does the digital economy promote the structural upgrading of the Chinese service industry? Journal of Quantitative & Technological Economics 40 (2) (2023) 90–112.
[30] T.L. Wu, W. Shao, How does digital economy drive industrial structure upgrading: an empirical study based on 249 prefecture-level cities in China, PLoS One 17 (11) (2023) e0277787.
[31] Q.W. Fu, How does digital technology affect manufacturing upgrading? Theory and evidence from China, PLoS One 17 (5) (2022) e0267299.
[32] D.X. Kan, L.J. Lyu, W.C. Huang, W.Q. Yao, Digital economy and the upgrading of the global value chain of China's service industry, Journal of Theoretical and Applied Electronic Commerce Research 17 (4) (2023) 1279–1296.
[33] X.C. Xu, M.H. Zhang, Research on the scale measurement of China's digital economy: based on the perspective of international comparison, China Industrial Economics (5) (2020) 23–41.
[34] Y.Z. Cai, X.X. Niu, Scale measurement and structural analysis of the value-added of China's digital economy, Soc. Sci. China (11) (2021) 4–30+204.
[35] J.Z. Zhang, W.Q. Zhao, B.D. Cheng, A.X. Li, Y.Z. Wang, et al., The impact of digital economy on the economic growth and the development strategies in the post-COVID-19 era: evidence from countries along the "belt and road", Front. Public Health 10 (2022) 856142.
[36] H. Mahmood, CO2 emissions, financial development, trade, and income in north America: a spatial panel data approach, Sage Open 10 (4) (2020).
[37] H. Mahmood, The spatial analyses of consumption-based CO2 emissions, exports, imports, and FDI nexus in GCC countries, Environ. Sci. Pollut. Control Ser. 29 (32) (2022) 48301–48311.
[38] H. Mahmood, N. Saqib, A.H. Adow, M. Abbas, FDI, exports, imports, and consumption-based CO2 emissions in the MENA region: spatial analysis, Environ. Sci. Pollut. Control Ser. 30 (25) (2023) 67634–67646.
[39] H. Mahmood, N. Saqib, A.H. Adow, M. Abbas, Oil and natural gas rents and CO 2 emissions nexus in MENA: spatial analysis, PeerJ 11 (2023) e15708.
[40] T.C. Li, Z.Y. Shi, D.R. Han, Does renewable energy consumption contribute to the development of low-carbon economy? Evidence from China, Environ. Sci. Pollut. Control Ser. 28 (39) (2021) 54891–54908.
[41] H. Mahmood, M. Furqan, N. Saqib, A.H. Adow, et al., Innovations and the CO2 emissions nexus in the MENA region: a spatial analysis, Sustainability 15 (13) (2023) 10729.
[42] Y.H. Zhao, Z.Y. Zhao, Z.L. Qian, L. Zheng, Is cooperative green innovation better for carbon reduction? Evidence from China, J. Clean. Prod. 394 (2023) 136400.
[43] Q.B. Guo, Y. Wang, X.B. Dong, Effects of smart city construction on energy saving and CO 2 emission reduction: evidence from China, Appl. Energy 313 (2022) 118879.
[44] J. Wang, K. Dong, X. Dong, F. Taghizadeh-Hesary, Assessing the digital economy and its carbon-mitigation effects: the case of China, Energy Econ. 113 (2022) 106198.
[45] W.X. Xu, J.P. Zhou, C.J. Liu, The impact of digital economy on urban carbon emissions: based on the analysis of spatial effects, Geogr. Res. 41 (1) (2022) 111–129.
[46] J.L. Liu, Q.H. Yu, Y.Y. Chen, J.G. Liu, The impact of digital technology development on carbon emissions: a spatial effect analysis for China, Resour. Conserv. Recycl. 185 (2022) 106445.
[47] K. Luo, Y.B. Liu, P.F. Chen, M.L. Zeng, Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt, Energy Econ. 112 (2022) 106127.
[48] Y.W. Lyu, W.Q. Wang, Y. Wu, J.N. Zhang, How does digital economy affect green total factor productivity? Evidence from China, Sci. Total Environ. 857 (2) (2023) 159428.
[49] Q. Xu, M.R. Zhong, M.Y. Cao, Does digital investment affect carbon efficiency? Spatial effect and mechanism discussion, Sci. Total Environ. 827 (2022) 154321.
[50] S. Kunkel, M. Matthess, Digital transformation and environmental sustainability in industry: putting expectations in Asian and African policies into perspective, Environ. Sci. Pol. 112 (2020) 318–329.
[51] Z.D. Shabani, R. Shahnazi, Energy Consumption, Carbon Dioxide Emissions, Information and Communications Technology, and Gross Domestic Product in Iranian Economic Sectors: a Panel Causality Analysis, 169, 2019, pp. 1064–1078.
[52] Z. Yang, W.J. Gao, Q. Han, L.Y. Qi, Y.J. Cui, Y.Q. Chen, Digitalization and carbon emissions: how does digital city construction affect China's carbon emission reduction? Sustain. Cities Soc. 87 (2022) 104201.
[53] A.M. Hao, Y.R. Hou, J.Y. Tan, How does digital village construction influences carbon emission? The case of China, PLoS One 17 (12) (2022) e0278533.
[54] Z.G. Li, J. Wang, The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China, J. Clean. Prod. 351 (2022) 131570.
[55] Y. Cheng, Y. Zhang, J.J. Wang, J.X. Jiang, The impact of the urban digital economy on China's carbon intensity: spatial spillover and mediating effect, Resour. Conserv. Recycl. 189 (2022) 106762.
[56] X.L. Hao, S.F. Wen, Y.H. Li, Y.P. Xu, Y. Xue, Can the digital economy development curb carbon emissions? Evidence from China, Front. Psychol. 13 (2022) 938918.
[57] L. Zhang, R.Y. Mu, Y.F. Zhan, J.H. Yu, L.Y. Liu, Y.S. Yu, J.X. Zhang, Digital economy, energy efficiency, and carbon emissions: evidence from provincial panel data in China, Sci. Total Environ. 852 (2022) 158403.
[58] C. Semeraro, A.G. Olabi, H. Aljaghoub, A.H. Alami, M. Al Radi, M. Dassisti, M. A. Abdelkareem, Digital twin application in energy storage: trends and challenges, J. Energy Storage 58 (2023) 106347.
[59] A. Polyanska, S. Savchuk, I. Zapukhliak, et al., Digital maturity of the enterprise as an assessment of its ability to function in industry 4.0, Lecture Notes in Mechanical Engineering (2022) 209–227.
[60] C. Park, S. Cho, W. Heo, Study on the future sign detection in areas of academic interest related to the digitalization of the energy industry, J. Clean. Prod. 313 (2021) 127801.
[61] J.Q. Wang, X.H. Nghiem, F. Jabeen, A. Luqman, M.L. Song, Integrated development of digital and energy industries: paving the way for carbon emission reduction, Technol. Forecast. Soc. Change 187 (2023) 122236.
[62] D.R. Han, Y.Y. Ding, Z.Y. Shi, Y. He, The impact of digital economy on total factor carbon productivity: the threshold effect of technology accumulation, Environ. Sci. Pollut. Control Ser. 29 (37) (2022) 55691–55706.
[63] H. Mahmood, M. Furqan, M.S. Hassan, S. Rej, The environmental Kuznets Curve (EKC) hypothesis in China: a review, Sustainability 15 (7) (2023) 6110.
[64] H. Mahmood, M.S. Hassan, S. Rej, M. Furqan, The environmental Kuznets Curve and renewable energy consumption: a review, Int. J. Energy Econ. Pol. 13 (3) (2023) 279–291.
[65] L. Chen, M.Z. Li, Q.Y. Xue, Realistic constraints and path selection of data element market construction, Reforma (1) (2023) 83–94.
[66] S.Y. Luo, N. Yimamu, Y.R. Li, H.T. Wu, et al., Digitalization and sustainable development: how could digital economy development improve green innovation in China? Bus. Strat. Environ. 32 (4) (2022) 1847–1871.
[67] X. Xiao, Y.D. Qi, Value dimension and theoretical logic of industrial digital transformation, Reforma (8) (2019) 61–70.
[68] M. Kolloch, D. Dellermann, Digital innovation in the energy industry: the impact of controversies on the evolution of innovation ecosystems, Technol. Forecast. Soc. Change 136 (2018) 254–264.
[69] J.Q. Wang, X.W. Ma, J. Zhang, X. Zhao, Impacts of digital technology on energy sustainability: China case study, Appl. Energy 323 (2022) 119329.
[70] Q. Xu, M.R. Zhong, Shared prosperity, energy-saving, and emission-reduction: can ICT capital achieve a "win-win-win" situation? J. Environ. Manag. 319 (2022) 115710.
[71] IPCC, IPCC Fourth Assessment Report: Climate Change 2007, Cambridge University Press, Cambridge, UK, 2007.
[72] T.C. Li, Z.Y. Shi, D.R. Han, Research on the impact of energy technology innovation on total factor ecological efficiency, Environ. Sci. Pollut. Control Ser. 29 (24) (2022) 37096–37114.
[73] H. Altintas, Y. Kassouri, The impact of energy technology innovations on cleaner energy supply and carbon footprints in Europe: a linear versus nonlinear approach, J. Clean. Prod. 276 (2020) 124140.
[74] Z.M. Yan, B.L. Zou, K.R. Du, K. Li, Do renewable energy technology innovations promote China's green productivity growth? Fresh evidence from partially linear functional-coefficient models, Energy Econ. 90 (2020) 104842.
[75] J. Ning, Q.R. Yin, A. Yan, How does the digital economy promote green technology innovation by manufacturing enterprises? Evidence from China, Front. Environ. Sci. 10 (2022) 967588.
[76] B.Q. Lin, Z. Li, Towards world's low carbon development: the role of clean energy, Appl. Energy 307 (2022) 118160.
[77] P. Tzeremes, E. Dogan, N.K. Alavijeh, Analyzing the nexus between energy transition, environment and ICT: a step towards COP26 targets, J. Environ. Manag. 326A (2023) 116598.
[78] M. Pagliaro, F. Meneguzzo, Digital management of solar energy en route to energy self-sufficiency, Global Challenges 3 (8) (2019) 1800105.

[79] P.Y. Chen, Is the digital economy driving clean energy development? -New evidence from 276 cities in China, J. Clean. Prod. 372 (2022) 133783.
[80] R.R. Li, L.J. Li, Q. Wang, The impact of energy efficiency on carbon emissions: evidence from the transportation sector in Chinese 30 provinces, Sustain. Cities Soc. 82 (2022) 103880.
[81] Q.X. Wang, A. Hu, Z.H. Tian, Digital transformation and electricity consumption: evidence from the Broadband China pilot policy, Energy Econ. 115 (2022) 106346.
[82] T. Zhao, Z. Zhang, S.K. Liang, Digital economy, entrepreneurship, and high-quality economic development empirical evidence from urban China, Journal of Management World 36 (10) (2020) 65–76.
[83] Y. Zhao, X.H. Chen, The relationship between the withdrawal of the digital economy's innovators, government interventions, the marketization level and market size based on big data, J. Enterprise Inf. Manag. 35 (4/5) (2022) 1202–1232.
[84] X.M. Yin, Z.Y. Lin, J. Chen, R. Zhao, The value ecosystem construction and market allocation mechanism of data elements, Sci. Technol. Prog. Policy 39 (22) (2022) 1–8.
[85] M.E. Porter, America's green strategy, Sci. Am. 264 (4) (1991) 193–246.
[86] L.P. Wang, Y. Long, C. Li, Research on the impact mechanism of heterogeneous environmental regulation on enterprise green technology innovation, J. Environ. Manag. 322 (2022) 116127.
[87] C.J. Liu, T. Feng, Y. Li, Network infrastructure construction, digital inclusive finance and digital divide: a policy effect analysis based on the establishment of "broadband China" demonstration cities, Finance Econ. (12) (2022) 103–116.
[88] M. Shahbaz, M.A. Destek, I. Okumus, A. Sinha, An empirical note on comparison between resource abundance and resource dependence in resource abundant countries, Resour. Pol. 60 (2019) 47–55.
[89] S. Che, J. Wang, Can environmental regulation solve the carbon curse of natural resource dependence: evidence from China, Resour. Pol. 79 (2022) 103100.
[90] X.L. Hao, Y.H. Li, S.Y. Ren, H.T. Wu, Y. Hao, The role of digitalization on green economic growth: does industrial structure optimization and green innovation matter? J. Environ. Manag. 325A (2023) 116504.
[91] P.M. Romer, Endogenous technological change, J. Polit. Econ. 98 (S) (1990) 71–102.
[92] W. Chen, Can Low-Carbon Development Force Enterprises to Make Digital Transformation? Business Strategy and the Environment, 2022.
[93] Dong, F., Hu, M.Y., Gao, Y.J., Liu, Y.J. et al. How does digital economy affect carbon emissions? Evidence from global 60 countries. Sci. Total Environ. 852, 158401.
[94] R.Y. Ma, Z.P. Zhang, B.Q. Lin, Evaluating the synergistic effect of digitalization and industrialization on total factor carbon emission performance, J. Environ. Manag. 348 (2023) 119281.
[95] A. Saia, Digitalization and CO2 emissions: dynamics under R&D and technology innovation regimes, Technol. Soc. 74 (2023) 102323.
[96] H.M. Li, R.Z. Xu, How does digital finance affect the efficiency of urban green economies? Evidence from China, Finance Res. Lett. 58 (2023) 104595.
[97] Y. Liu, Y.X. Xie, K.Y. Zhong, Impact of digital economy on urban sustainable development: evidence from Chinese cities, Sustain. Dev. (2023) 2656.
[98] H. Mahmood, Trade, FDI, and CO2 emissions nexus in Latin America: the spatial analysis in testing the pollution haven and the EKC hypotheses, Environ. Sci. Pollut. Control Ser. 30 (6) (2023) 14439–14454.
[99] Z.L. Wen, B.J. Ye, Analyses of mediating effects: the development of methods and models, Adv. Psychol. Sci. 22 (5) (2014) 731–745.
[100] B.E. Hansen, Threshold effect in non-dynamic panels: estimation, testing, and inference, J. Econom. 93 (2) (1999) 345–368.
[101] L. Anselin, D.A. Griffith, Do spatial effects really matter in regression analysis? Pap. Reg. Sci. 65 (1) (2010) 11–34.
[102] X.D. Yang, Q.Y. Ran, J.N. Zhang, Urban innovation, fiscal decentralization and environment pollution, Ind. Econ. Res. (3) (2020) 1–16.
[103] J.N. Zhang, Y.W. Lyu, Y.T. Li, Y. Geng, Digital economy: an innovation driving factor for low-carbon development, Environ. Impact Assess. Rev. 96 (2022) 106821.
[104] C.Y. Zhao, W.C. Wang, X.S. Li, How does digital transformation affect the total factor productivity of enterprises? Finance & Trade Economics 42 (7) (2021) 114–129.
[105] X.D. Chen, X.X. Yang, Does the digital transformation improve the independent and controllable ability of industrial chain? Business and Management Journal 44 (8) (2022) 23–39.
[106] W.Q. Zhao, J. Hu, S.G. Zhao, Factor allocation efficiency industry and industry upgrading in China, Journal of Quantitative & Technological Economics 37 (12) (2020) 146–162.
[107] F. Wu, H.Z. Hu, H.Y. Lin, X.Y. Ren, Enterprise digital transformation and capital market performance: empirical evidence from stock liquidity, Journal of Management World 37 (7) (2021) 130–144+10.
[108] P.B. Guo, X.J. Zhou, D. Li, et al., Predicament and its solution in the transformation of coal resource based economy: a perspective of energy technology innovation, China Soft Science (7) (2013) 39–46.
[109] A. Sagar, Technology Innovation and Energy, Harvard University, 2004.
[110] J. Wang, S.L. Zhang, Q.J. Zhang, The relationship of renewable energy consumption to financial development and economic growth in China, Renew. Energy 170 (2021) 897–904.
[111] M.A. Destek, A. Asian, Renewable and non-renewable energy consumption and economic growth in emerging economies: evidence from bootstrap panel causality, Renew. Energy 111 (2017) 757–7563.
[112] D. Shi, S.L. Li, Emissions trading system and energy use efficiency: measurement and empirical evidence for cities at and above the prefecture level, China Industrial Economics (9) (2020) 5–23.
[113] G. Fan, X.L. Wang, L.W. Zhang, H.P. Zhu, Marketization index for China's provinces, Econ. Res. J. (3) (2003) 9–18, 89.
[114] Q. Wei, A. Wang, J. Wang, The rise of China's coastal regions: the power of the market, Econ. Res. J. 49 (8) (2014) 170–183.
[115] W.H. Pan, Z.C. He, H.Y. Pan, Research on spatiotemporal evolution and distribution dynamics of digital economy development in China, China Soft Science 10 (2021) 137–147.
[116] B.M. Gu, J.G. Liu, Q. Ji, The effect of social sphere digitalization on green total factor productivity in China: evidence from a dynamic spatial Durbin model, J. Environ. Manag. 320 (2022) 115946.
[117] H. Wang, Y.Y. Li, W.F. Lin, W.D. Wei, How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China, J. Environ. Manag. 325A (2023) 116524.
[118] J.J. Zheng, X.W. Wang, Can mobile information communication technologies (ICTs) promote the development of renewables? Evidence from seven countries, Energy Pol. 149 (2021) 112041.
[119] Y.R. Guan, Y.L. Shan, Q. Huang, H.L. Chen, D. Wang, K. Hubacek, Assessment to China's recent emission pattern shifts, Earth's Future. Earths Future 9 (11) (2021) e2021EF002241.
[120] X.L. Wang, L.P. Hu, G. Fan, Report on Market Index by Province in China (2021), Social Sciences Academic Press, Beijing, 2021.
[121] J.A. Schumpeter, Capitalism, Socialism and Democracy, Harper & Brothers, New York, 1942.
[122] J. Zhao, Q.Z. Jiang, X.C. Dong, K.Y. Dong, H.D. Jiang, How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China, Energy Econ. 105 (2022) 105704.
[123] M. Yi, Y.F. Liu, M.S. Sheng, L. Wen, Effects of digital economy on carbon emission reduction: new evidence from China, Energy Pol. 171 (2022) 113271.
[124] Q. Liang, S.P. Xiao, M.X. Li, Digital economy development, spatial spillover and innovation quality growth: the threshold effect test of market efficiency, Shanghai Journal of Economics (9) (2021) 44–56.
[125] Y.W. Yang, Q.Y. Liang, Digital economy, environmental regulation and green eco-efficiency-Empirical evidence from 285 cities in China, Front. Environ. Sci. 11 (2023) 1113293.
[126] X.M. Yin, L.Y. Qi, J.L. Zhou, The impact of heterogeneous environmental regulation on high-quality economic development in China: based on the moderating effect of digital finance, Environ. Sci. Pollut. Control Ser. (2022).
[127] Y. Su, Y.Q. Yu, Spatial agglomeration of new energy industries on the performance of regional pollution control through spatial econometric analysis, Sci. Total Environ. 704 (2020) 135261.
[128] M.M. Tao, S. Poletti, L. Wen, M.S. Sheng, et al., Appraising the role of the digital economy in global decarbonization: a spatial non-linear perspective on globalization, J. Environ. Manag. 347 (2023) 119170.
[129] H.Y. Hu, Q.Z. She, Does digital transformation of manufacturing reduce the embodied carbon intensity on exports, Journal of International Trade (7) (2022) 36–52.
[130] Y. Xie, Z. Chen, F. Boadu, H.J. Tang, How does digital transformation affect agricultural enterprises' pro-land behavior: the role of environmental protection cognition and cross-border search, Technol. Soc. 70 (2023) 101991.