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The Digital Economy and Real Economy: The Dynamic Interaction Effect and the Coupling Coordination Degree

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Abstract: This article aims to analyze the interplay between the digital economy (DE) and the real economy (RE), examining how they impact each other in terms of empowerment and supply effects. The study object is China from 2011 to 2021. This study applies the panel vector autoregressive model (PVAR). The study's findings underscore a delayed empowerment effect within the DE. While DE growth has the potential to substantially enhance the future overall expansion of the tangible economy, it might concurrently dampen the short-term structural balance of the latter. However, the supply effect in the RE mode exhibits a similar delay. The time-lagged factors relating to the tangible economy's total growth and structural fine-tuning play a pivotal role in fostering the progress of DE. Self-enhancement mechanisms significantly influence the overall growth of the tangible economy. However, this mechanism does not have the same significance in regard to enhancing structural coordination. Although the tangible economy's expansion can catalyze structural refinement, the inverse relationship—where structural enhancement profoundly fuels tangible economic growth—does not hold true to a substantial extent. By assessing the overall degree of coupling and coordination between the DE and the tangible economy, it becomes apparent that these two domains are not tightly integrated. Instead, they exist in a fundamentally coordinated state, with a year-on-year upwards trend in their alignment, albeit at a modest pace. Furthermore, this coupling coordination degree displays a progressively diminishing trend from the southeastern coastal regions to the western interior, revealing a pronounced spatial imbalance. The contribution of this paper lies in its comprehensive enhancement of the theoretical framework and empirical research in the integration of energy and digital economy, addressing sustainable development, regional economic disparities, and practical policy implications to support future strategies for blending digital advancement with renewable energy utilization.

Keywords: digital economy; real economy; dynamic interaction; coupling coordination

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1. Introduction

The digital economy (DE) refers to the segment of the economy that is primarily driven by digital technologies and the internet [1]. It encompasses all economic activities that rely on digital information, electronic transactions, and the use of digital devices. These include e-commerce, online services, digital content creation and distribution, data analytics, and artificial intelligence [2]. DE is characterized by its reliance on information and communication technologies (ICTs). It is highly dynamic, rapidly evolving, and often capitalizes on data-driven insights and automation. Businesses and individuals within the DE leverage digital tools and platforms to facilitate transactions, streamline processes, and create new forms of value [3,4]. The real economy (RE), also known as the traditional or physical economy, encompasses all economic activities related to the production, distribution, and consumption of tangible goods and physical services [5]. It includes sectors such as manufacturing, agriculture, construction, transportation, healthcare, and retail, where physical products and human labor play a central role. RE relies on physical resources, human labor, and traditional supply chains [6]. It has a long history and is deeply rooted in the production and delivery of goods and services that people use in their daily lives. Unlike DE, which is primarily digital, RE deals with the tangible and physical aspects of economic activities. Digital technologies have become integral to RE, enhancing productivity, supply chain management, and customer engagement. Conversely, the RE provides physical infrastructure for the digital world, such as data centers and logistics for e-commerce. The DE is reshaping the RE. Industries are digitizing operations, automating tasks, and incorporating data analytics and AI into their processes [7]. This transformation can result in greater efficiency, cost savings, and new opportunities, but it also poses challenges such as job displacement and cybersecurity risks. Access to DE is not universal, and disparities in digital access and skills can exacerbate economic inequality. Bridging this digital divide is essential to ensure that the benefits of DE reach a broader population.

The distinction between DE and RE is indeed nuanced, and the integration of digital technologies into traditional industries can blur the boundaries between the two. The conceptualization of DE by the Cyberspace Administration of China [8], which includes both digital industrialization and industry digitalization, reflects this complexity. Digital industrialization generally refers to industries that are primarily engaged in producing digital technologies, digital infrastructure, and digital services [9,10]. Examples include software development, cloud computing, and digital platform services. This sector aligns well with the definition of the DE, as it involves the direct creation of digital goods and services. The industry digitalization concept involves the application of digital technologies to traditional industries, a process often referred to as digital transformation. It includes the integration of digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics into sectors such as manufacturing, agriculture, and healthcare [11,12]. While the core of these industries is RE, their digitalization contributes to efficiency, productivity, and innovation [13–15], thus becoming a significant part of the DE value chain. The misalignment between these definitions arises from the interplay and convergence of these sectors:

- Overlap and integration: Industry digitalization represents the penetration of digital technologies into RE. While the industries themselves (such as manufacturing or agriculture) are part of the RE, the digital tools, processes, and systems integrated into these industries are part of the DE. Therefore, industry digitalization is a hybrid area where DE and RE intersect and interact.
- Value addition and measurement: The value added by digital technologies to traditional industries contributes significantly to DE metrics. For instance, a smart factory equipped with IoT devices and AI for predictive maintenance may still be categorized under manufacturing (RE), but the value generated through increased productivity and efficiency due to digital technologies contributes to the growth of DE.

In essence, the categorization by the Cyberspace Administration of China [8] recognizes the transformative impact of digital technologies on traditional industries and includes this under the umbrella of DE. This perspective acknowledges that the value generated through digitalization in traditional sectors is an integral part of the contemporary digital economic landscape. It also reflects a more holistic approach to understanding the economy in the digital age, where the boundaries between DE and RE are not rigid but rather fluid and interconnected.

The integration of DE and RE is crucial for developing a modern industrial system and achieving sustainable growth, particularly through innovation [16]. Recent academic studies have focused on this integration, which involves combining digital resources and technologies with traditional industries. Researchers such as Szczepańska-Woszczyna et al. [17] and Ginevicius et al. [18] emphasize its importance, while Hong and Ren [19] and Miskiewicz [20] describe it as a blend of digital resources, technologies, and sharing platforms, highlighting the increasing significance of data in production. They suggest that this integration requires a robust support system driven by digital technologies, a demand-driven production process, and a financial system to operate smoothly. Tian and Zhang [21] noted that infrastructure, data resources, and platform companies are key to this process. Research by Ren et al. [22] shows that combining DE and RE can reduce costs, boost productivity, and modernize supply chains. Zhang et al. [23] used a spatial Durbin model to demonstrate how this integration can upgrade industrial structures. Studies by Hao et al. [24], Koibichuk et al. [25], and Hakimova et al. [26] revealed that it also fosters green practices by increasing investment in research and technology.

However, there are still gaps in the existing studies. This study is motivated by the need to deepen the understanding of the intricate interplay between DE and RE, realms that are increasingly intertwined but not fully comprehended. While existing research has predominantly focused on the external effects and individual contributions of DE and RE, this study aims to bridge a significant gap by investigating their interactive relationships. Utilizing panel vector autoregression (PVAR), this research ventures beyond surface-level analyses to unravel the synergistic dynamics between these two critical sectors of the economy. The data used in this study mainly come from the China Statistical Yearbook, China City Statistical Yearbook, China Third Industry Statistical Yearbook, National Bureau of Statistics, provincial statistical yearbooks, and Peking University Digital Inclusive Finance Index.

A notable contribution of this study is its exploration of the growth and structural coordination of RE in the context of the burgeoning DE, an aspect that remains largely underexplored in the literature. Although recent studies, such as those by Guo et al. [27] have initiated discourse on the coordination between DE and RE, this paper takes a leap forward. It provides a granular examination of the influence of DE on the structural and functional facets of RE, thereby enriching the prevailing narrative and enhancing our comprehension of complex economic tapestry.

This longitudinal approach facilitates a nuanced analysis of the dynamic interactions and coordination mechanisms between DE and RE. By dissecting temporal patterns and regional disparities, this paper sheds light on the evolving landscape of economic integration, offering valuable insights for policymakers and stakeholders aiming to harmonize digital advancement with real-world economic progress.

2. Literature Review

2.1. Empowering Effect of the DE

The development of RE has been significantly empowered by DE [28,29]. As an innovative integrated economy, DE revitalizes existing economic structures and stimulates growth. This is achieved through leveraging new digital infrastructure, abundant digital elements, innovative products, and the provision of financial services [30]. Zhou [31] confirmed the transformative impact of DE on rural consumption upgrading in China. Using data from the China Family Panel Studies, Zhou [31] provides empirical evidence on how DE catalyzes the enhancement of rural household consumption, highlighting the potential of digitalization in spurring economic development in rural areas. This study represents a critical exploration of the role of DE in bridging urban–rural divides and enhancing living standards in less developed areas. In a broader context, Remeikiene et al. [32] expand the discourse by conceptualizing the digital shadow economy. This research offers a theoretical framework that sheds light on the intricate dynamics of DE beyond formal economic boundaries, indicating the pervasive nature of digital technologies in shaping economic interactions and structures. Nham et al. [33] explore the nonlinear effects of digitalization on export activities across European countries. This empirical investigation illuminates the intricate relationship between DE and international trade, revealing how digital advancements influence export dynamics and contribute to the economic performance of nations. Concurrently, DE transforms the operation and business models within the RE sector. It restructures resources across various RE sectors [34–37], leading to an optimized structural framework for the RE industry. The impact of DE on the empowerment of the RE sector manifests in several ways:

1. Investments in new digital infrastructures, such as 5G, the industrial internet, and the Internet of Things [20,38], significantly enhance production efficiency in the RE sector. Studies indicate that intelligent manufacturing systems, which integrate artificial intelligence and IT technologies, improve both production efficiency and quality [39,40]. Additionally, digitized supply chain management systems optimize supply chain efficiency and boost enterprise productivity. The implementation of such infrastructure also facilitates a "creative destruction" process [41], optimizing the industrial structure of RE and promoting digitization, networking, and green development.
2. As a crucial production factor in the digital era, data offer vast support to RE. Data possess unique multiplicative and matching capabilities compared to traditional factors such as capital and labor. The deep integration of data with other production factors enhances various RE development processes, from R&D to sales and services. This integration maximizes production factor benefits and allows for effective supply matching in the RE sector.
3. DE contributes to RE growth and structural transformation through digital industrialization and industrial digitization. Digital industrialization, which relies on digital technologies, nurtures emerging knowledge-intensive industries, in turn supporting RE industrial optimization and transformation. Studies [42–44] underscore the importance of digital skills and digital trust in fostering workplace efficiency and employability, aligning with the observed regional differences in DE and RE integration. Additionally, Veckalne and Tambovceva [44] emphasize the role of digital transformation in promoting sustainable development, further highlighting the potential for digital technologies to enhance economic synergy between DE and RE. Digital integration with existing industries forms new business models, reduces operational costs, and enhances quality of life [45]. Industrial digitization encourages traditional industries to adopt digital technologies, promoting innovation and efficiency throughout the industry value chain.
4. Digital finance, underpinned by networked and information systems, expands the scope of traditional financial services [46–48]. It integrates deeply with digital technology, enabling efficient customer acquisition and risk management. Digital finance eases financing challenges for real enterprises, lowers financial service thresholds, and directs social capital towards high-tech and green industries, supporting the transformation of the RE sector [49].
5. AIGC has emerged as a transformative force in the RE landscape [50]. In manufacturing, for instance, AI-driven content generation accelerates design processes, enabling rapid prototyping and customization [51]. In the service sector, AIGC tools are employed for generating reports, forecasts, and analyses, thereby enhancing efficiency and reducing human error. A notable example is the use of AIGC in financial services for generating market analysis reports. The AIGC significantly bolsters innovation and product development [52]. By analyzing vast datasets, AI algorithms can identify market trends and consumer preferences, guiding companies in developing tailored products. In the automotive industry, AIGC aids in designing vehicles by proposing innovative features and styles based on current trends and safety standards.

2.2. Promotion Effect of the RE

RE "promotes" DE development, providing fundamental support and the ultimate direction for its development. The growth and structural optimization of RE can stimulate the construction of new digital infrastructure. With the digitization, networking, intelligence, collaboration, and integration of various sectors in RE, there is an increasing demand for digital infrastructure, necessitating the urgent construction of new digital infrastructure that is faster, larger in scale, more efficient, environmentally friendly, and interconnected [53,54]. For example, the development of industries such as the Internet of Things [20], smart manufacturing, and smart cities requires the support of new digital infrastructure. The development of emerging industries represented by modern services and high-tech industries also heavily relies on the construction of new internet infrastructure. Therefore, while pursuing operational efficiency improvement, cost reduction, and risk mitigation, RE also provides more development space and opportunities for DE. Furthermore, the RE provides data inputs for the DE. As a practical subject and important foundation of DE, RE accumulates massive amounts of data through rich application scenarios. The production activities and transactions of REs generate a large amount of RE data, including logistics data [55], supply chain data, and financial data. These data inputs are essential components of the DE, which requires the support and input of these RE data. RE can also improve production processes and enhance product quality and service levels through digitization and informatization, thereby generating more valuable data inputs and providing further support for DE. Finally, the market demand for RE is the driving force behind DE development. As the foundation of RE, the demand for products and services in the market mainly comes from businesses, industries, and consumers. The RE provides market demand, and the DE meets this demand through data analysis and technological innovation. The application of digital technology can also improve the efficiency and quality of various sectors within RE, thereby promoting its development and innovation. RE helps realize seamless connections between consumers and products, creates more job opportunities, stimulates social investment and expenditure, and enhances the vitality and viability of DE.

DE empowers the RE, while the RE supplies the DE. DE enriches and expands the essence and boundaries of RE, restructuring its operational and business models and bringing about dual development in terms of "quantity" and "quality". The rapid development of RE drives the construction of new infrastructure in DE and provides data inputs and market demand, thereby stimulating DE development. Therefore, DE and RE exhibit dynamic interactions and coordinated development.

The existing studies outline a symbiotic relationship between DE and RE, emphasizing how digital technologies empower economic growth and structural transformation. The analyzed studies highlight DE's role in revitalizing infrastructures, enhancing data utilization, and fostering digital finance, while RE supports this development by driving demand for digital innovations and providing essential data inputs. However, these studies also suggest areas for further exploration, including the socioeconomic impacts of digitalization, regulatory challenges, and the sustainability of digital advancements. Based on this, the following research hypothesis was checked within this study:

Hypothesis 1. *Accelerating digital integration in lagging sectors through targeted policy interventions will enhance the synchronization between the digital economy and the real economy, thereby improving the overall coupling coordination and driving sustainable economic growth in China*.

3. Materials and Methods

3.1. Model Construction

Based on past studies [48–52], the panel vector autoregressive (PVAR) model was chosen in this study to investigate the dynamic interaction effects between DE and RE systems:

$$Y_{i,t} = \alpha_0 + \sum_{j=1}^{p} \beta_j Y_{i,t-j} + \theta_i + \delta_t + \epsilon_{i,t} \quad (1)$$

where $Y_{i,t} = (DEI, EGR, SCO)^T$ is the vector of dependent variables; DEI is the DE development level; EGR is the total growth of the RE; SCO is the coordination of the RE structure; α_0 is a column vector representing the intercept terms of the model; p is the number of lagged terms in the model; β_j is the parameter vector to be estimated in the model; θ_i denotes the individual fixed effects; δ_t represents the time fixed effects; and $\epsilon_{i,t}$ represents the random error term.

The fundamental strength inherent in the PVAR model lies in its capacity to capture the intricate interactions among variables, all while evading the need for strict predefined conditions when estimating studies [56–60]. This inherent flexibility bestows a heightened ability to faithfully portray the dynamic interrelationships that unfurl between variables over time. Unlike traditional econometric models, which often require stringent assumptions about the data and the relationships among variables, the PVAR model operates with greater adaptability. It allows for the inclusion of multiple lags of the dependent and independent variables, providing a more comprehensive picture of how variables influence each other over various time horizons. This makes the PVAR model particularly suitable for complex economic systems where the interactions among variables are not immediate but unfold over several periods. Additionally, the PVAR model's structure accommodates both fixed and random effects, enabling it to account for unobserved heterogeneity across different entities in the panel data. This is crucial in studies where regional, sectoral, or temporal differences might significantly impact the variables of interest. By incorporating these effects, the PVAR model ensures that the unique characteristics of each entity are considered, leading to more accurate and robust results. Furthermore, the model's ability to handle endogeneity—a common issue in economic data where explanatory variables are correlated with the error term—adds to its robustness. Through techniques such as the Generalized Method of Moments (GMM), the PVAR model can address endogeneity concerns, providing reliable parameter estimates that reflect true causal relationships rather than spurious correlations. The PVAR model also excels in its use of impulse response functions and variance decomposition analyses. These tools allow researchers to explore how a shock to one variable impacts other variables over time and to quantify the contribution of each variable to the fluctuations in the system. This level of detailed analysis is invaluable for policymakers and researchers aiming to understand the long-term effects of policy interventions or economic changes. Before embarking on the analysis utilizing the PVAR model, a preliminary step involves scrutinizing the stationarity of each variable. This precautionary measure aims to avert potential issues arising from spurious regression, which can stem from nonstationary data. To maintain the reliability of the findings, this study undertook panel unit root tests employing three distinct methodologies: the Levin–Lin–Chu (LLC) test, the augmented Dickey–Fuller unit-root test (ADF-Fisher), and the Im–Pesaran–Shin (IPS) test. To ascertain the optimal lag order for the test across the observed sample years, the criteria of the MBIC and MQIC were employed. To clarify the short-term dynamic impact and causality between the three variables, a Granger causality test is conducted based on the constructed PVAR model. Furthermore, to explore the specific short-term and long-term causal relationships between the three variables, GMM estimation and impulse response analysis of the variables are needed, building upon the causality test.

The coupling coordination model is adopted to measure the degree of coordination between DE development and RE:

$$C_{i,t} = 2 \times \left[\frac{U_{1,i,t} \times U_{2,i,t}}{\left(U_{1,i,t} + U_{2,i,t}\right)^2} \right]^{1/2} \tag{2}$$

where $C_{i,t}$ is the coupling degree function between the DE and the RE in province i during year t, with values ranging from 0 to 1; $U_{1,i,t}$ is the DE development in province i during year t; and $U_{2,i,t}$ is the RE development in province i during year t.

In addition, considering the situation where the contribution levels of DE and RE are low and close, to avoid the occurrence of coupling degrees that deviate from realistic meanings, the coupling coordination model is further enhanced based on the coupling degree function (Equation (3)).

$$\begin{cases} T_{i,t} = \alpha U_{1,i,t} + \beta U_{2,i,t} \\ D_{i,t} = \sqrt{C_{i,t} \times T_{i,t}} \end{cases} \tag{3}$$

where $T_{i,t}$ is the level of integrated development between the DE and the RE in province i during year t; α and β are the contribution degrees of the DE and the RE subsystems to the overall system, respectively; and $D_{i,t}$ is the coupling coordination degree between the DE and the RE in province i during year t.

3.2. Indicator Selection and Data Sources

To assess the intricate interdependencies that exist between the DE and the RE, the following indicator framework was used:

Considering that DE mainly empowers RE development through digital infrastructure, data elements, digital products, and financial services, this study adopts a measurement framework for the level of digital economic development based on previous research [61,62]. The framework is divided into four secondary indicators: digital infrastructure, data element support, data element services, and data–financial services. By combining these dimensions, DE development can be comprehensively and systematically described. The comprehensive index of DE development is measured using the entropy weight TOPSIS method. The specific indicator system is shown in Table 1.

Table 1. Indicator system for measuring the integration of the DE and the RE (source: developed by the authors).

Primary Indicator	**Secondary Indicator**
DE	
Digital infrastructure	Fiber optic cable length/land area (10,000 km/10,000 sq. km) Number of mobile phone base stations (units) Mobile phone penetration rate (%) Number of internet broadband access points (units) Number of internet users (people) Number of internet domain names (units)
Data element support	Number of websites owned by enterprises (units) E-commerce sales revenue (100 million yuan) Number of websites (10,000) Mobile internet access traffic (10,000 GB)
Digital product services	Number of information transmission and software industry personnel (10,000 people) Regional software business income (10,000 yuan) Number of information service industry employees (10,000 people) Information service industry output value (100 million yuan) Telecommunication services total volume (100 million yuan) Postal and telecommunication services total volume (100 million yuan)
Digital financial services	Peking university digital inclusive finance index
RE	
Total growth	Agricultural value added/gross domestic product (%) Industrial value added/gross domestic product (%) Construction industry value added/gross domestic product (%) Transportation and telecommunication industry value added/gross domestic product (%) Wholesale and retail trade value added/gross domestic product (%) Accommodation and catering industry value added/gross domestic product (%)
Structural coordination	Theil index (%) Ratio of tertiary industry output value to secondary industry output value (%)

RE development supplies DE, and development is a concept that combines both "quantity" and "quality". It includes not only the growth of the economic aggregate but also the overall improvement in the economic structure. Therefore, based on the research of Li et al. [63], RE development is measured using two indicators: the growth of the economic aggregate and the coordination of the economic structure. The growth of the economic aggregate is measured by the proportion of value-added contributions from agriculture, industry, construction, transportation, wholesale and retail, and accommodation and catering sectors to the gross domestic product. This excludes the proportion of the finance and real-estate sectors in the gross domestic product based on the classification and processing methods proposed by Huang [64] and Wu et al. [65]. The coordination of economic structure mainly measures the interrelation and proportionality among various components of the national economy, including ownership structure, demand structure, and industrial structure. Considering data availability and representativeness, this study measures the coordination of the RE structure using the index of industrial structure. The level of coordination is measured by the Theil index, which represents the rationalization of industrial structure, and the ratio of the value of tertiary industry to the value of secondary industry, which represents the advancement of industrial structure [66]. The specific indicators are shown in Table 1.

This study conducted research based on panel data collected from 31 provinces in China (excluding Hong Kong, Macau, and Taiwan) from 2011 to 2021. Missing values are supplemented using linear interpolation. The data used in this study mainly come from the *China Statistical Yearbook*, *China City Statistical Yearbook*, *China Third Industry Statistical Yearbook*, National Bureau of Statistics, provincial statistical yearbooks, and Peking University Digital Inclusive Finance Index.

4. Results

The results of the descriptive statistics are shown in Table 2. The DE development index is calculated by normalizing the data of each indicator, determining the weights of the primary indicators via the principal component analysis, determining the weights of the secondary indicators via the entropy value method and calculating the weighted sum. The data for total growth of the RE are obtained by deducting the value added of the finance and real estate sectors. The coordination of the RE structure is obtained by averaging the Theil index and the industrial structure advancement index. Additionally, considering the impact of heteroscedasticity on the model, logarithmic transformation is applied to all variables in this study. It stabilizes the variance and makes the distribution more symmetrical, which can lead to more reliable estimation results. Furthermore, logarithmic transformation makes the dataset scale invariant, allowing for more meaningful comparisons. After transformation, differences can be interpreted in terms of percentage changes rather than absolute changes [67].

Table 2. Descriptive statistics of panel data.

Symbols	Variable	Obs.	Mean	Min	Max	St. Dev.
DEI	DE development level	341	0.3118	0.1410	0.575	0.8678
EGR	Total growth of the RE (in CNY 100 million)	341	21,756.55	561.60	102,506.9	18,594.83
SCO	Coordination of the RE's Structure	341	0.6757	0.2636	2.622	0.3608

Note: Obs.—observations; Max—maximum value; Min—minimum value; St. Dev.—standard deviation.

The results of the LLC, ADF-Fisher, and IPS tests are shown in Table 3, indicating that the DE, total growth, and structural coordination variables passed the stationarity test.

Table 3. The findings of the stationarity test results.

Variable	ln(DEI)	ln(EGR)	n(SCO)
LLC	−6.4469 *	−7.4049 *	−3.8039 *
ADF-Fisher	7.1564 *	7.5051 *	6.0038 *
IPS	−2.0670	−2.3772 *	−0.6427
Results	Pass	Pass	Pass

Note: * indicates statistical significance at the 1% level.

Notably, the focus of the IPS test is not on the p-value but on achieving the minimum t-bar value. The table indicates only the t-bar values, and all of them are the minimum values. In the PVAR model, determining the lag order of variables is crucial for model specification and results. The optimal lag order of variables in the PVAR model can be determined based on criteria such as MAC, MBIC, and MQIC. Generally, the lag order corresponding to the minimum value (indicated by *) in each criterion is considered the optimal lag order in that criterion. The results for the optimal lag order test for the observed sample years are shown in Table 4. It is evident that both the MBIC and MQIC criteria suggest the same optimal lag order, which is 1. Therefore, the final determination for the optimal lag order of variables in the model is 1.

Table 4. Optimal lag order (source: developed by the authors).

Optimal Lag Order	MAIC	MBIC	MQIC
1	−8.2089	−6.88136 *	−7.67636 *
2	−7.47463	−5.90209	−6.84159
3	−6.9399	−5.07084	−6.18488
4	−8.1415	−5.90429	−7.2349
5	−8.76441 *	−6.05478	−7.66382

Note: * indicates statistical significance at the 1% level.

The results of the Granger causality test are shown in Table 5.

Table 5. Results of the Granger causality test.

Variable	Null Hypothesis	Chi-Square	Test Result
ln(DEI)	ln(DEI) is not the cause	1.4034	Rejected
ln(DEI)	ln(EGR) is not the cause	3.2632	Rejected
ln(DEI)	None of them is the cause	4.5642	Rejected
ln(EGR)	ln(SCO) is not the cause	1.208	Rejected
ln(EGR)	ln(DEI) is not the cause	2.8082	Rejected
ln(EGR)	None of them is the cause	4.903	Rejected
ln(SCO)	ln(EGR) is not the cause	2.8683	Rejected
ln(SCO)	ln(DEI) is not the cause	2.2674	Rejected
ln(SCO)	None of them is the cause	6.8857 *	Accept

Note: * indicates statistical significance at the 1% level.

The findings (Table 5) show that, except for the inability of the DE development index and total growth of the RE to explain the structural coordination of the RE, the null hypothesis is rejected for the other cases. This indicates that, in the PVAR model of this study, there is clear bidirectional Granger causality among the three variables, demonstrating significant interactive effects between them. Based on the previous examination and processing of variables and panel data, this study applies the optimal lag order of 1 to perform a Generalized Method of Moments (GMM) estimation on the relationship between DE and RE in 31 provinces. The aim is to explore the dynamic interaction effects among the DE, the total growth of the RE, and the structural coordination of the RE. The findings (Table 6) show that, for DE, the coefficients for the lagged DE development level and the total growth of RE are both significant and positive. This indicates that the growth of RE drives DE development.

Table 6. GMM estimation results.

Variables	h_ln(DEI)	h_ln(EGR)	h_ln(SCO)
L. h_ln(DEI)	2.479 **	1.955 **	1.197
	(2.51)	(1.98)	(1.51)
L. h_ln(EGR)	1.185 *	−0.575	−0.897 ***
	(1.81)	(−0.74)	(−2.69)
L. h_ln(SCO)	−0.341 **	−0.370	0.635 ***
	(−2.18)	(−1.10)	(2.75)

Note: ()—t values; *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In the equation for the total growth of RE, the coefficient for DE is significant and positive. This suggests that DE can increase RE and contribute to the growth of total RE. In the equation for the structural coordination of RE, the coefficient for the DE development level is significant but negative. This implies that, in the short term, DE will primarily drive the digitization of lifestyle services such as catering and accommodation, while industries with weaker foundations, such as manufacturing and agriculture, face challenges in achieving digital integration, resulting in short-term structural imbalances.

Impulse response functions are used to analyze and test the relationships and impact levels among the DE, total growth of the RE, and structural coordination of the RE. From Figure 1, the three subplots along the diagonal show that, when there is an increase in the DE, it exhibits a strong positive response to its own impulse shock, which fades away around the 10th period. Similarly, when there is a one-standard-deviation shock in the total growth of the RE, it initially shows a strong positive response, which quickly declines and nearly disappears by the fourth period. The structural coordination of the RE initially reflects a strong response to its own impulse shock but then quickly declines.

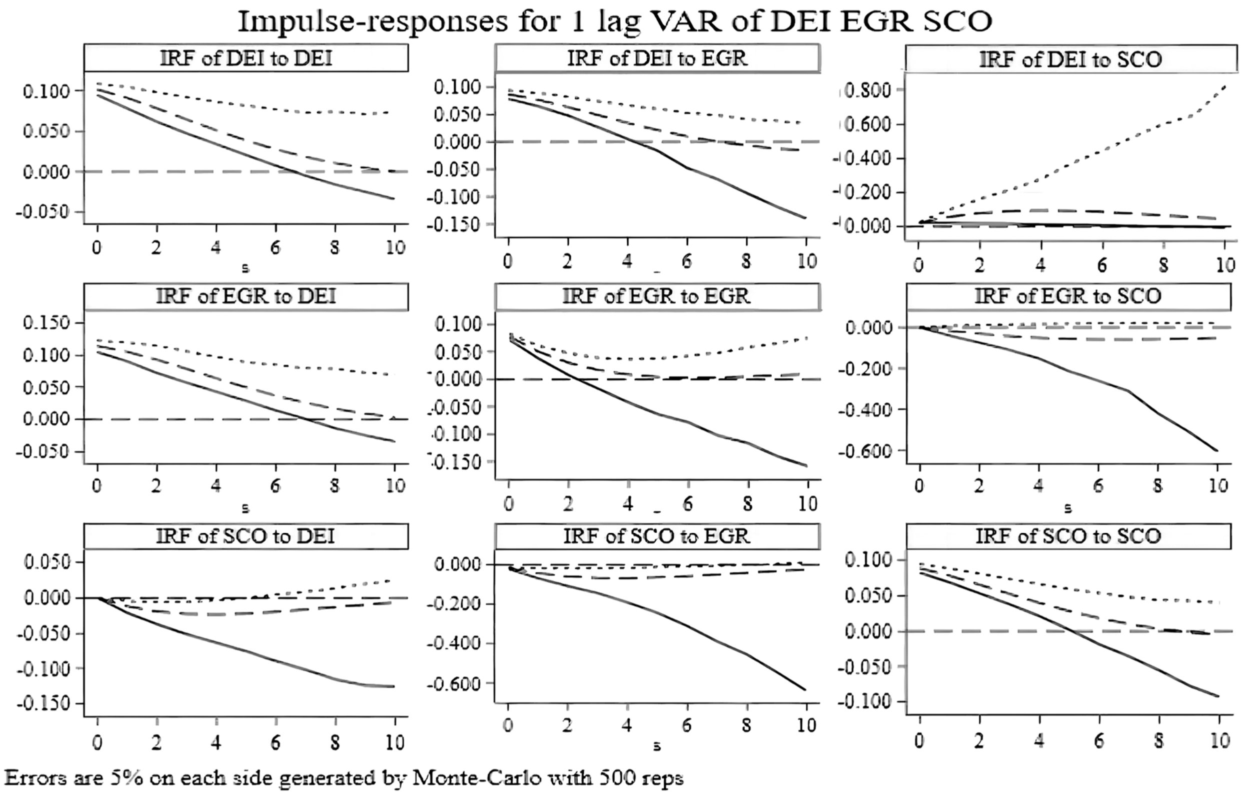

Figure 1. Impulse response results.

In terms of the mutual influence between variables, observing the two plots on the right side of the first row in Figure 1 reveals that the DE has a peak response around the first period and a positive sign when there is a one-standard-deviation shock in the total growth of the RE. This indicates that the growth of RE plays a driving role in DE development. In comparison, the response of the DE to a one-standard-deviation shock in the structural variation in the RE remains relatively low over all periods, following a weak parabolic trajectory, with a peak response around the fifth period, all positive. This indicates a positive promoting effect of the structural coordination of RE on DE development.

Furthermore, the first plot in the second row of Figure 1 shows the response of the total growth of the RE to a one-standard-deviation shock in the DE. This demonstrates that DE development significantly promotes the growth of RE. Similarly, the first plot in the third row shows the response of the structural coordination of the RE to the DE. The trajectory starts out negative and gradually becomes positive, suggesting that, in the short term, DE may cause a lack of coordination in the RE structure, consistent with earlier analyses. However, in the long term, the DE can optimize the structure of the RE.

To further evaluate the impact of model disturbances on the shocks of endogenous variables and the contribution of different structural shocks during the process of changes among variables, a variance decomposition analysis was conducted on the PVAR model. This analysis examined the contribution of the interplay between the DE, total growth of the RE, and structural coordination of the RE in the observed sample provinces for the 1st, 10th, 20th, and 30th periods. From the variance decomposition results in Table 7, it can be observed that, excluding the impact of DE on itself, both the total growth of RE and structural coordination have a certain influence on DE, with a combined effect of 52.8% in the 30th period. The total growth of the RE starts with a contribution of 22.6% in the 1st period and remains stable at approximately 25% in subsequent periods, reaching 26.5% in the 30th period.

Table 7. Variance decomposition results.

Dependent Variable	Period	Shock Variable		
		ln(DEI)	ln(EGR)	ln(SCO)
ln(DEI)	1	0.253	0.226	0.521
	10	0.499	0.241	0.261
	20	0.485	0.252	0.263
	30	0.481	0.265	0.263
ln(EGR)	1	0.000	0.423	0.577
	10	0.652	0.094	0.254
	20	0.647	0.100	0.253
	30	0.642	0.105	0.254
ln(SCO)	1	0.000	0.000	1.000
	10	0.443	0.094	0.495
	20	0.454	0.061	0.485
	30	0.454	0.062	0.485

The impact of structural coordination on the DE starts at 52.1% and remains at approximately 26% in subsequent periods. Furthermore, the primary shock variable for the total growth of the RE is the DE. It initially had no effect but stabilized at approximately 64% in the 10th, 20th, and 30th periods, indicating a significant influence of the DE on the total growth of the RE. Finally, in the early periods, the impact of structural coordination is mainly self-induced.

However, during the observed periods, the impact of the DE on structural coordination continues to increase and remains stable at approximately 45% in the sample period.

The empirical results of the PVAR model mentioned above indicate the existence of dynamic interaction effects between the DE and the RE. However, the PVAR model does not reflect the degree of coordination between the two. Therefore, in this study, a coupling coordination model was further selected to measure the coupling coordination between the DE and the RE. The comprehensive development index of the DE is used to measure the DE, while the RE development includes total growth and structural coordination, both of which are equally important for RE development. Therefore, the mean value of the standardized total growth and structural coordination is used to represent the level of development of the RE. Additionally, in determining the parameters α and β, which represent the contribution rates of the DE and the RE to the overall system, a value of 0.5 is chosen for both parameters, referring to the study by Guo and Quan [27]. Regarding the discriminant criteria for coupling coordination, Liao [68] referred to ten-level classification criteria, and the intervals of each level were expanded. From a temporal perspective, between 2011 and 2021, the coupling coordination between DE and RE was not high but showed a gradual upwards trend with a slowing growth rate. The average coupling coordination of DE and RE in 31 Chinese provinces increased from 0.366 in 2011 to 0.663 in 2021 (Figure 2).

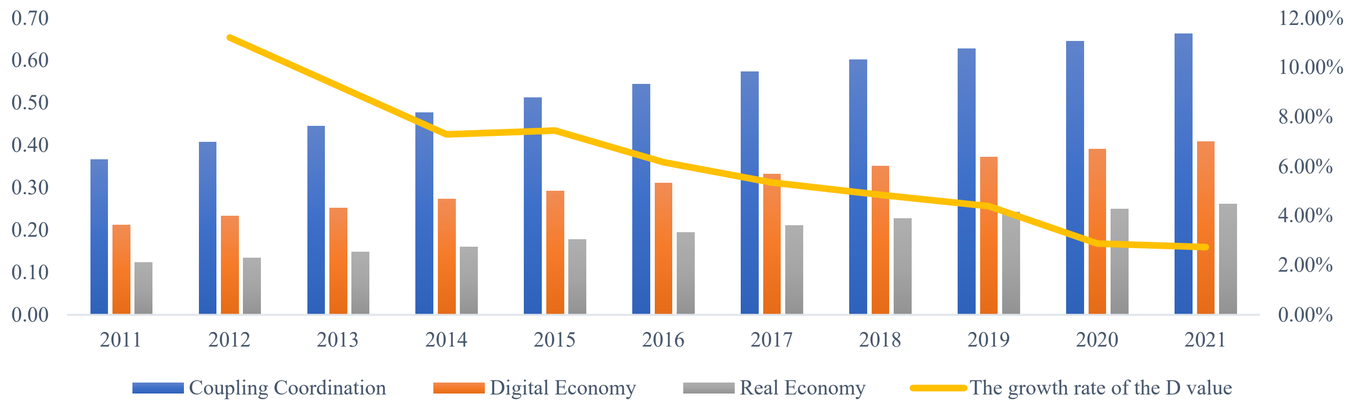

Figure 2. Changes in the coupling coordination between DE and RE from 2011 to 2021.

This upwards trend indicates that, over the 11-year period, the DE and the RE experienced continuous growth. DE has created new economic growth points and business models through digital technologies and data elements, empowering RE. Moreover, RE has contributed to DE development through continuous economic growth and structural coordination. The contributions of DE and RE have been increasing annually, and their dynamic interaction has collectively enhanced the coupling coordination between DE and RE. However, the average coupling coordination value of 0.53 suggests that the integration level between the two is only at a basic coordination state, and the growth rate has slowed. The growth rate declined from 11.214% in 2012 to 2.737% in 2021.

There are several possible reasons for this: (1) The integration of DE and RE follows a pattern of starting with easier sectors and progressing to more challenging sectors. Currently, it is still in the early stage of low-level applications. The integration initially prioritized industries such as catering, accommodation, and transportation before transitioning to sectors such as agriculture and industry, where the integration difficulty is greater. This has led to a slowdown in the integration growth rate. (2) Key digital core technologies are currently lacking and have significant shortcomings, posing constraints on the integration of the digital and real sectors. (3) The awareness of data element ownership is weak, and there is still a lack of regulations and established standards. This limits the flow of data between the DE and the RE. (4) Some real sectors face difficulties in digital transformation due to limited awareness or constraints in technology and capital. This makes the integration of the digital and real sectors more challenging.

From a spatial perspective, during the sample period, the coupling coordination between DE and RE in China gradually decreased from the southeastern coastal areas to the western inland regions, broadly conforming to the pattern known as the Hu Huanyong line. From 2011 to 2021, the regions with the highest average coupling coordination were East China and South China, with values of 0.622 and 0.610, respectively, indicating a moderate coordination level. The central and northeast regions had average values of 0.588 and 0.547, respectively, indicating a basic coordination state. The southwest region had the lowest coupling coordination index, with an average value of only 0.381, indicating a moderate imbalance.

These patterns are highly correlated with the uneven development of digitalization between East China, South China, Central China, and the relatively less developed regions of Southwest, Northeast, and Northwest China. Advanced manufacturing and services are concentrated in the eastern regions, while the northeastern and western regions have a concentration of heavy industrial bases, making digital transformation more challenging. This contributes to the observed “east–high, west–low” characteristic of the integration of DE and RE.

To illustrate the spatial differentiation of coupling coordination, this study selected the spatial distribution status of digital and real integration in 2011, 2016, and 2021, as shown in Table 8. Regarding individual provinces, in 2013, the proportions of provinces categorized as severely imbalanced, moderately imbalanced, in a basic coordination state, and moderately coordinated were 3.23%, 58.06%, 32.26%, and 3.23%, respectively.

Table 8. The spatial pattern evolution of the coupling coordination between the DE and the RE.

Year	Severe Imbalance	Moderate Imbalance	Basic Coordination	Moderate Coordination	High Coordination
2011	Inner Mongolia	Shanxi, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Hunan Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Qinghai, Xinjiang	Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Henan, Hubei, Guangdong, Chongqing	Beijing	
2016		Inner Mongolia, Qinghai, Ningxia	Tianjin, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shanxi, Gansu, Xinjiang	Shanghai, Jiangsu, Zhejiang Shandong, Henan, Hubei Guangdong	Beijing
2021		Ningxia	Shanxi, Inner Mongolia, Liaoning Jilin, Tibet, Shanxi, Gansu, Qinghai, Xinjiang	Tianjin, Hebei, Heilongjiang, Anhui, Fujian Jiangxi, Shandong, Henan Hubei, Hunan, Guangxi Hainan, Chongqing, Sichuan Guizhou, Yunnan	Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong.

As of 2016, Inner Mongolia, which previously experienced significant imbalance, had transitioned to a state of moderate imbalance. In the same timeframe, Beijing progressed from moderate coordination to a high level of coordination. The distribution of imbalances shifted, with the proportions of moderate imbalance and basic and moderate coordination reaching 9.68%, 64.52%, and 22.58%, respectively. This suggests that a majority of provinces shifted towards a state of basic coordination after 2016. Rapidly until 2021, Beijing, Shanghai, Guangdong, Zhejiang, and Jiangsu achieved coupling coordination values surpassing 0.8. This advancement placed them at an exceedingly high level of coupling coordination, signifying a substantial deepening of integration between the DE and the RE within these provinces.

The level of coupling coordination in each province is closely related to its gross domestic product (GDP). In 2020, Beijing, Shanghai, Guangdong, Jiangsu, and Zhejiang ranked among the top five in terms of per capita GDP, while regions with relatively lower economic development levels, such as Inner Mongolia, Gansu, Ningxia, Xinjiang, Qinghai, and Tibet, were at the lower end.

The results show that the continuous growth in the digital economy and real economy has created new economic growth points and business models, boosting overall economic development. However, the average coupling coordination value of 0.53 indicates that their integration is still at a basic level, with a significant slowdown in the growth rate from 2012 to 2021. Regional disparities are evident, with higher integration in economically advanced regions like Beijing and Shanghai, and lower integration in less developed areas, highlighting the uneven digital transformation across China. The positive correlation between higher GDP and better integration suggests that economic development fosters stronger DE and RE synergy. These findings emphasize the need for targeted policies to bridge the digital divide and promote balanced regional economic growth.

5. Discussion

This article explores the logical mechanism of the integration and development of DE and RE, using the PVAR model to analyze the dynamic interactive effects between the growth of DE, the growth of RE, and the coordination of the RE structure. Furthermore, this article constructs a coupling coordination model of DE and RE, calculates the digital–real integration index, and depicts the spatiotemporal evolution pattern of the coordination of digital–real coupling in China.

The data indicate that DE is the primary driver of total growth in RE, with its influence stabilizing at approximately 64% by the 10th, 20th, and 30th periods. This shows a significant impact of the DE on overall RE growth. The impact of the DE on structural coordination continues to grow throughout the observed periods, ultimately stabilizing at around 45% during the sample period. However, this significant influence does not manifest immediately but rather over time, signaling a period before the full advantages of digital integration are seen within the RE. For example, the growth of DE from 0.21 in 2011 to 0.40 in 2021 highlights a steady but gradual boost in RE, showcasing both the potential and the hurdles of weaving digital innovations into conventional sectors. The quantification of the impact of DE on the overall economy and structural coordination aligns with the study of Chao et al. [53], who discussed the comprehensive measurement and regional differences of China's new economy, emphasizing the significant role of digital advancements in economic development. However, this study further elucidates the temporal lag in realizing the benefits of digital integration, a nuanced aspect that adds depth to our understanding of DE's gradual influence, resonating with Guo and Quan's [27] exploration of the integration development between DE and RE, yet providing more granular growth metrics.

The role of RE in fueling DE growth, which contributes approximately 52%, underscores the vital importance of traditional economic expansion and structural fine-tuning in propelling digital progress. This effect, evidenced by the increase in RE growth metrics from 0.12 in 2011 to 0.26 in 2021, stresses the necessity of cultivating RE growth to spark digital breakthroughs. The time gap in this reciprocal growth cycle accentuates the need for deliberate planning and ongoing investment in the core components of RE.

The gradual increase in coupling coordination from 0.36 in 2011 to 0.66 in 2021 indicates a positive trajectory towards tighter integration between the DE and RE. Despite the upwards trajectory, a slowing pace of growth—shifting from rapid to more gradual increases—points to growing difficulties in further integration. This trend signifies the continual but inconsistent advancement towards aligning digital and conventional economic sectors, suggesting that targeted efforts could improve coordination efficiency. The gradual rise in coupling coordination and the identified regional disparities provide quantitative support for Hu et al.'s [28,30] examination of the driving factors and regional differentiation of integrated development. Unlike previous studies that broadly address the need for targeted policy measures, this research quantitatively demonstrates the variances in integration levels, offering a concrete basis for region-specific strategies.

The difference in integration levels across regions, as seen in the decreasing coupling coordination from the southeast coast to the inland west, underscores significant regional imbalances. For instance, the higher average coupling coordination scores in East China and South China (0.622 and 0.610, respectively) strongly differ from Southwest China's lower score of 0.381. These discrepancies highlight the uneven integration landscape across China, influenced by the industrial foundation, digital infrastructure, and local development strategies. The assignment of numerical values to regional coupling coordination provides a basis for targeted policies to address the digital divide, refining the approach suggested by Guo et al. [46] with specific data-driven regional strategies.

This study presents a novel analytical approach to examining the dynamic interplay between China's DE and RE by utilizing the PVAR model and a sophisticated coupling coordination model. This study innovatively quantifies the reciprocal effects and bidirectional Granger causality between DE growth, RE growth, and RE structural coordination, supported by a rigorous statistical framework including logarithmic transformation and variance decomposition analysis. The findings reveal a complex, evolving landscape of DE-RE integration across China that is marked by spatial disparities and an upwards yet uneven trend in coupling coordination, providing critical insights for future sustainable development and digitalization strategies in the energy sector.

6. Conclusions

By integrating the detailed quantitative and numerical conclusions drawn from the analysis of China's growth strategy, specific policy recommendations can be tailored to leverage the identified trends to maximize economic development and digital integration. The following are some recommendations based on the numerical findings:

Given the significant quantitative impact of the digital economy on China's overall economic growth and structural coordination, policy measures should focus on sectors where digital technologies can yield the highest economic dividends. China could establish a prioritization framework that targets sectors based on their potential for digital enhancement, measured by their contribution to GDP and employment. Investment in digital infrastructure should be dynamically allocated to these priority sectors to maximize the impact on the broader economy. This involves channeling resources into sectors that show the most promise for digital transformation, thereby optimizing economic returns and fostering long-term growth. Additionally, China's fast-track digital integration programs should not only focus on narrowing the gap between DE and RE but also aim to increase China's position in global DE. This involves prioritizing sectors with the potential for international leadership, such as artificial intelligence, 5G telecommunications, and green technologies. By fostering innovation and excellence in these areas [13], China can enhance its global competitiveness and lead in setting international standards for digital technologies. A 50% increase in digital tool utilization in the manufacturing sector by 2025 could spur more immediate benefits of digital integration. Such initiatives could result in increased productivity, reduced costs, and improved quality of outputs, thereby reinforcing China's economic prowess. Moreover, these targets should be accompanied by regular monitoring and evaluation to ensure progress and adjust strategies as needed. This continuous assessment would allow policymakers to identify challenges and areas needing improvement, thereby making the digital integration process more adaptive and resilient. Establishing key performance indicators (KPIs) and benchmarks for digital infrastructure projects can provide a clear roadmap for development and success, ensuring that the investments yield tangible benefits. Furthermore, collaboration between the government, private sector, and international partners could amplify the effects of digital integration. By fostering a collaborative ecosystem, China can leverage diverse expertise and resources to drive innovation and achieve its digital economy goals. Establishing partnerships with leading tech companies and research institutions can accelerate the adoption of cutting-edge technologies and best practices, positioning China at the forefront of the global digital landscape.

The substantial 52% contribution of RE to DE development suggests a strategic approach to scaling support based on sectors' ability to propel digital growth. This could involve creating a performance-based funding model in which RE sectors that show strong potential for digital innovation receive increased support and incentives. This model can encourage sectors within RE to actively adopt digital technologies, thereby accelerating the mutual reinforcement cycle between DE and RE [14]. This model would reward sectors that demonstrate significant progress in digital transformation with increased funding, fostering a competitive environment that drives innovation and efficiency. Additionally, improving access to funding for digital initiatives within the RE is crucial. This could involve offering low-interest loans or grants specifically for digital technology projects, enabling businesses to invest in new tools and systems without the burden of substantial upfront costs. Ensuring that companies have the financial resources needed to pursue digital innovations can significantly enhance their capacity to integrate advanced technologies into their operations. Offering tax breaks for digital innovation is another potent incentive. By reducing the financial burden associated with investing in digital technologies, businesses are more likely to undertake such initiatives. Tax incentives could be structured to reward various aspects of digital innovation, such as research and development, implementation of new digital systems, and training programs for employees to ensure effective use of new technologies. Upgrading digital infrastructure in industrial areas is also essential to support this transformation. This involves ensuring that high-speed internet, cloud computing services, and other necessary digital infrastructure components are readily available and reliable. Enhanced digital infrastructure enables businesses to implement and leverage digital technologies more effectively, leading to improved productivity and competitiveness. Furthermore, fostering a collaborative ecosystem between the government, private sector, and academic institutions can amplify the impact of these initiatives. By working together, these stakeholders can share knowledge, resources, and best practices, creating a supportive environment for digital innovation. Government policies should also facilitate public–private partnerships to drive large-scale digital projects that can benefit entire sectors.

The gradual increase in synchronization between the digital economy and the real economy, as indicated by the rise in coupling coordination from 0.36 in 2011 to 0.66 in 2021, underscores the need for accelerated efforts in key areas. To continue this positive trend, policies should focus on developing digital skills, innovation capabilities, and technological infrastructure in sectors that are lagging in synchronization but are pivotal for China's economic strategy. To address the digital skills gap, targeted education and training programs are essential. These programs should be designed to equip the workforce with the necessary digital competencies, such as coding, data analysis, and digital project management. Collaborating with educational institutions and industry leaders to develop comprehensive curricula can ensure that the skills taught are relevant and up to date. Additionally, offering incentives for ongoing professional development can help maintain a continuously evolving skill set within the workforce. Enhancing innovation capabilities requires a multi-faceted approach. First, fostering a culture of innovation within businesses and organizations is crucial. This can be achieved through initiatives that encourage creative problem-solving and the adoption of new technologies. Providing grants and funding for research and development (R&D) projects can also stimulate innovation. Establishing innovation hubs and incubators where startups and established companies can collaborate on digital solutions can further drive technological advancements. Investing in technological infrastructure is fundamental for supporting DE-RE integration. This involves upgrading existing infrastructure and expanding access to high-speed internet, advanced computing facilities, and secure data storage solutions. Special attention should be given to sectors that are critical to China's economic strategy but are currently lagging in digital adoption. By prioritizing infrastructure improvements in these sectors, the overall efficiency and productivity can be significantly enhanced. Special programs designed to fast-track digital adoption in lagging sectors can be highly effective. These programs could include pilot projects that demonstrate the benefits of digital integration, thereby encouraging broader adoption. Providing tailored support and resources, such as consulting services and technical assistance, can help businesses navigate the complexities of digital transformation. Monitoring and evaluating the progress of these programs through key performance indicators (KPIs) will ensure that they are meeting their objectives and can be adjusted as needed.

The stark regional variations in DE-RE integration levels, particularly the lower integration figures in Southwest China compared to East China and South China, necessitate regional policy adjustments. Tailored strategies should be deployed that consider each region's unique industrial composition, infrastructure status, and economic development level. For regions lagging in digital integration, targeted initiatives such as digital skill development programs, infrastructure improvement projects, and innovation incubators can help bridge this gap [15]. By aligning regional development strategies with national priorities, China can ensure that digital transformation acts as a catalyst for harmonizing growth across the country.

This study represents a significant advancement in the domain of sustainable development, focusing on the intricate relationship between DE and RE in China. It breaks new ground by integrating these two pivotal sectors, unveiling their interdependent dynamics and mutual reinforcement capabilities through the innovative use of the PVAR model. This model allows us to analyze not only the dynamic interactions between DE and RE but also the substantial impact of DE on the economic volume and structural coordination of RE. The empirical evidence provided illustrates the bidirectional empowering and promoting effects between these sectors, emphasizing the substantial influence of DE on RE growth and structural optimization. Methodologically, this study introduces a cutting-edge coupling coordination model for DE and RE, coupled with a meticulously calculated digital–real integration index. This novel approach not only represents a methodological leap but also provides a comprehensive spatiotemporal analysis, offering a granular view of the evolution and regional distribution of digital-real coupling. The strategic policy recommendations derived from the findings are particularly noteworthy, as they provide actionable insights and a clear direction for harnessing the potential of DE and RE. These recommendations are instrumental in shaping future infrastructure, technology, and financial services, ultimately guiding the sustainable and coordinated development of regional economies.

The scientific value added by this research is multidimensional. This study not only contributes to the theoretical framework of energy and DE integration but also paves the way for future empirical research. This study's focus on sustainable development, regional economic disparities, and practical policy implications enriches the discourse in this field, offering a robust foundation for future inquiries and strategies aimed at achieving a harmonious blend of digital advancement and renewable energy utilization.

The limitation of this study is the absence of a heterogeneity analysis for evaluating the impact of DE on RE across various industries. This research approach treats the influence of DE on the RE sector uniformly, without delving into the diverse, industry-specific interactions that may occur. Industries such as agriculture, industry, construction, transportation, wholesale and retail, and accommodations all have unique operational characteristics, technological adoption rates, and environmental footprints. Therefore, the impact of DE on RE is likely to be highly variable among these sectors. For example, the influence of DE in promoting renewable energy in the energy-intensive industrial sector could be significantly different from its impact in the accommodation industry, where energy demands and digital integration strategies are distinct. This gap in the literature indicates a crucial area for future investigations.

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