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Green Innovation Ecosystem Drives Enhancement of Energy Resilience in China: Exploratory Study Based on Dynamic Qualitative Comparative Analysis

Ru Fa and Yuli Liu *

School of Economics and Management, North University of China, Taiyuan 030051, China; 20170088@nuc.edu.cn
* Correspondence: sz202409018@st.nuc.edu.cn

Abstract

In recent years, with the growing intensity of extreme weather events, imbalances in energy supply and demand, and frequent regional conflicts, the stability of our energy systems faces increasing challenges. Against this backdrop, the green innovation ecosystem can optimize the energy system's structure and operational efficiency by promoting multi-actor interaction and multi-element synergy, thereby enhancing its resilience. Accordingly, this study aims to reveal how the green innovation ecosystem drives improvements in energy resilience (ER) through factor configurations and to identify the pathways leading to high-ER outcomes. To address this, this study constructs a research framework of the "core layer–environmental layer–supporting layer" for the green innovation ecosystem, and selects seven conditional variables, namely dual green innovation, multidimensional environmental regulation, green finance, and digital infrastructure. Based on official Chinese statistics, panel data from 30 provinces were compiled, and the dynamic qualitative comparative analysis (QCA) method was used to analyze how multiple factors interacted from 2016 to 2022 to achieve high ER from a spatiotemporal perspective. The results show that: (1) There is no single necessary condition for achieving high ER. (2) Dual green innovation and public participation in environmental regulation play a universal role in achieving high ER. They are combined with green finance, market-based environmental regulation, and digital infrastructure, forming three configuration pathways for achieving high ER. (3) No significant time effect is observed. (4) Pronounced spatial heterogeneity exists. The eastern region focuses on the green finance-enabled pathway, the central region has a high coverage of all three pathways, and the western region has relatively weak overall adaptability. Based on these findings, this study argues that enhancing ER depends on the coordinated allocation of multiple factors, and there is no single optimal pathway. Policymakers should adopt a configurational mindset and select appropriate combinations of elements in light of regional development conditions to enhance ER.

Keywords: dual green innovation; environmental regulation; green finance; digital infrastructure; allocation effect; energy resilience

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Academic Editor: Andrea Nicolini

Received: 17 November 2025
Revised: 3 January 2026
Accepted: 4 January 2026
Published: 8 January 2026

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1. Introduction

Energy is a fundamental basis for industrial production and people's lives, and a strategic foundation for national development and security [1]. Against the backdrop of climate change and the energy demand crisis, the global energy landscape is undergoing profound changes. Traditional energy systems face unprecedented structural challenges,

requiring an urgent transition to more flexible and sustainable energy solutions. Currently, global energy consumption has been increasing annually [2], energy price volatility is intensifying [3], and fossil fuel reserves are depleted and unevenly distributed, highlighting the urgency of energy development. To address this increasingly difficult situation, the United Nations and other relevant international organizations have explicitly proposed carbon-neutrality and environmental sustainability goals in international agreements such as the SDGs [4].

Furthermore, as a significant global energy producer and consumer [5], China has always placed energy development at the core of its national strategy. At the 75th session of the United Nations General Assembly, China made a clear commitment to peak carbon emissions by 2030 and to achieve carbon neutrality by 2060. However, with continued economic growth and rising energy demand, China's energy system faces three significant challenges: first, a coal-dominated energy structure results in high carbon emissions [6]; second, high dependence on imported oil and gas resources makes the supply system vulnerable to exogenous shocks [7]; and third, frequent extreme weather events and regional imbalances exacerbate the mismatch between energy supply and demand [8,9]. The problems above expose the energy system's vulnerability and instability, underscoring its limitations in responding to complex shocks. Against this backdrop, enhancing Energy Resilience (ER) can help overcome the current predicament facing the energy system [10].

ER describes an energy system's capacity to sustain core functions and recover from multiple shocks and disruptions [11]. The existing literature on ER mainly addresses two research strands: indicator construction and the examination of influencing factors. Currently, some scholars use single indicators and comprehensive indicators to measure ER. Common single indicators include energy efficiency [12]. However, the results of single-indicator assessments have certain limitations, struggling to reflect the comprehensive performance of the energy system under multiple shocks. In contrast, constructing a comprehensive indicator system can more comprehensively assess ER. From a multidimensional perspective, some studies have assessed ER by considering energy endowment, social, environmental, and economic dimensions [13]. Other scholars have focused on energy sustainability, comprehensively assessing ER from three dimensions: energy efficiency, renewable energy, and energy access [14].

Current studies on factors influencing ER primarily focus on single factors such as green finance, artificial intelligence, energy consumption trading systems, and digital global supply chains. Studies show that green finance can significantly strengthen ER by promoting green technology innovation and industrial transformation [15]. Furthermore, scholars have discussed the influence of artificial intelligence on ER at the city, provincial, and national levels. Artificial intelligence has a positive effect on urban ER at both the production and consumption ends [16]. Artificial intelligence technology innovation can promote the development of green finance, thereby enhancing ER across China's provinces [13]. Artificial intelligence can encourage the digital economy's development and assist in industrial restructuring, effectively mitigating energy vulnerability and thus enhancing the ER of G20 countries [17]. Energy consumption trading systems can also improve ER by driving green and low-carbon technologies and digital technology innovation, and industrial structure upgrading. However, involvement in digital global value chains undermines energy system resilience [18].

A review of the literature reveals a lack of unified measurement standards for ER indicators. Existing indicators fail to account for the whole dynamic closed-loop process of the energy system's response to shocks, thereby limiting their comprehensiveness and accuracy. In addition, most existing studies adopt traditional regression methods, which primarily focus on examining the net effect of a single factor on ER. Such approaches are

limited in revealing the synergistic effects of multiple influencing mechanisms and often fail to capture the dynamic characteristics of the evolution of influencing mechanisms over time. Consequently, this has led to insufficient attention to the temporal dimension and the evolutionary characteristics of causal relationships in ER research. At the same time, improving ER is a dynamic and complex process involving multiple stakeholders, factors, and stages, and breakthroughs are difficult to achieve by relying solely on traditional technical means or single policy tools.

As an application of innovation ecosystems in the field of green development, green innovation ecosystems possess ecological, open, and collaborative features [19]. Green innovation refers to innovations in processes, management, organization, and services related to green products or technologies, to achieve harmonious coexistence between humans and the environment. Faced with increasing environmental pressures and the practical needs of high-quality economic development, the concept of green development has gradually been integrated into traditional innovation ecosystems, forming green innovation ecosystems that differ from conventional innovation in terms of benefits and goals. Currently, the academic community mainly studies green innovation ecosystems from three aspects. The first is the connotation of green innovation ecosystems. Madsen conceptualizes the green innovation ecosystem as a resource-based, collaborative arrangement that supports organizational actors in conducting green technology innovation [20]. Zeng et al. describe the green innovation ecosystem as a complex, dynamically evolving system in which innovation elements circulate among innovation actors and their surrounding environment, thereby enhancing green innovation capacity and facilitating green technological advancement [21]. Although the academic community has not yet reached a consensus on the conceptual definition of a green innovation ecosystem, existing definitions all emphasize the importance of green innovation. Secondly, from a structural perspective, a green innovation ecosystem is generally composed of innovation actors, innovation resources, and the surrounding innovation environment [22]. Among them, innovation actors, as the prominent participants in the system, promote the cyclical flow of innovation resources such as policies, resources, information, technology, and new knowledge, thus facilitating green innovation activities. The innovation environment is an essential condition for ensuring the growth, evolution, cooperation, and symbiosis of innovation actors [23]. Innovation resources are vital to the innovation ecosystem and support the technology absorption of innovation actors [24]. Thirdly, in functional terms, the green innovation ecosystem stimulates green innovation within firms by providing managerial, structural, and technological support for green technology development. Adner and Kapoor point out that innovation ecosystems play a crucial role in technological innovation [25]. Chin [26], from a dynamic capability perspective, verifies that green innovation ecosystems promote enterprise green innovation through the communication and coordination mechanisms of participant networks.

Green innovation ecosystems align with green and low-carbon development goals, aiming to achieve environmental and social benefits and offering a new research perspective on improving ER. However, no research has directly explored the role of green innovation ecosystems in improving ER. Therefore, we attempt to understand this from the perspectives of green innovation and innovation ecosystems. From the standpoint of green innovation, green orientation and sustainable development goals provide direction for energy system transformation [27], while green innovation is the main pathway to achieving this transformation [28]. The core driving force of green innovation stems from technological progress [29], which helps optimize the energy system from production to consumption. Specifically, on the production end, green innovation enhances the diversity of energy supply by developing clean energy [30,31]. On the consumer side, energy

efficiency is improved through green technology substitution, energy-saving renovations, and industrial structure upgrading [32]. From the perspective of the innovation ecosystem, improved ER also depends on the synergistic effects of multiple stakeholders and factors [33,34]. Multiple stakeholders interact around factors such as policy, technology, capital, and information, forming a collaborative network of knowledge flow, resource sharing, and value co-creation. This collaborative network can optimize the allocation of energy resources [35] and provide emergency guarantees during energy supply disruptions, thereby ensuring the stable operation of the energy system [36]. Overall, green innovation injects vitality into the energy system, while the innovation ecosystem provides structural support. The green innovation ecosystem formed by their integration can promote improvements in energy system resilience.

Therefore, this study, based on a holistic perspective of the green innovation ecosystem, employs a configurational approach to explore the specific pathways through which the green innovation ecosystem drives ER enhancement. The following three questions are key: First, given that the green innovation ecosystem comprises multiple elements, how can these elements be coordinated and configured to drive ER enhancement? Second, against the backdrop of uneven regional development in China, how do differences in resource endowments, policy environments, and innovation foundations across regions affect ER enhancement? Finally, how can the impact of time on configuration pathways be captured? To address these questions, this study utilizes provincial panel data from China from 2016 to 2022 and employs a dynamic qualitative comparative analysis (dynamic QCA) method to conduct an empirical investigation. This method differs from traditional linear regression methods in that it can identify different combinations of conditions that lead to the same result [37]. Furthermore, compared to the fsQCA method, dynamic QCA introduces a time dimension, thereby better revealing the multi-pathway effects of green innovation ecosystems driving ER enhancement.

This study makes three main contributions. First, it incorporates dynamic QCA into ER research and examines how green innovation ecosystems shape ER from a configurational perspective rather than through isolated effects. Second, this study constructs a four-dimensional evaluation system of resistance, absorptive capacity, recovery capacity, and adaptive capacity, which quantifies the conceptual ER and provides a reference for a more comprehensive assessment of the performance of energy systems at different stages in response to disturbances. Third, this study is based on provincial-level samples in China, ensuring the universality of its conclusions within the country and offering valuable insights for global energy governance.

2. Theoretical Framework

This study, by combining the connotations and functions of the green innovation ecosystem [38], divides it into a core layer, an environmental layer, and a supporting layer to analyze the synergistic relationships among its elements clearly [21,39]. The core layer centers on innovation activities [40], in which diverse innovation actors form a symbiotic and competitive relationship through the flow and exchange of green knowledge and information, thereby promoting the formation and accumulation of green innovation [21]. The environmental layer provides a supportive innovation environment, offering essential elements for the growth, evolution, cooperation, and symbiosis of green innovation actors, ensuring the orderly progress of green innovation [39]. The supporting layer provides essential resources for innovation, facilitating innovation activities and promoting the generation, diffusion, and application of green innovation [41].

2.1. Green Innovation Core Layer and ER

The key factor for the stable development of a green innovation ecosystem is technological innovation [29]. Achieving technological innovation often requires enterprises, universities, and research institutions to continuously conduct core activities, such as green technology R&D, product transformation, and knowledge creation through mutual exchange and collaboration, thereby providing a crucial driving force for the system [42]. Green technology innovation is mainly divided into two modes: technological breakthrough and technological optimization. These two modes correspond to radical green innovation (RGI) and incremental green innovation (IGI), respectively, together constituting "dual green innovation" [43]. This study argues that the core layer of the green innovation ecosystem comprises dual green innovation activities carried out by actors such as enterprises, universities, and research institutions through industry-academia-research collaboration [44].

The core layer of green innovation enhances ER primarily through two paths. First, it is driven by RGI, which promotes significant technological changes and systematic restructuring of development paradigms through technological breakthroughs in the energy sector, thereby fundamentally enhancing the diversified supply capacity of the energy system and improving ER. For example, offshore floating wind power technology can overcome the limitations of water depth and wind speed, enabling large-scale clean energy development in deep-sea areas [45]. Second, ER enhancement is driven by IGI. Technological optimization in the energy sector involves refining and improving the efficiency of existing energy systems, enhancing system response efficiency, adaptability, and buffering and recovery efficiency against extreme disturbances, thereby improving ER. For instance, distributed energy storage technology can respond to load demands in milliseconds during grid emergencies, ensuring a stable power supply in critical sectors such as healthcare and communications [46].

2.2. Green Innovation Environment Layer and ER

In a green innovation ecosystem, the innovative behaviors of diverse stakeholders are profoundly influenced by their environment. Related research suggests that environmental regulations adjust continuously with technological development and different economic stages, exhibiting a dynamic, phased effect over time [47] and having a long-term impact on the behavior of innovation stakeholders [48]. Specifically, sound environmental regulations, supported by government oversight, market incentives, and public participation, can govern green innovation activities and, to a large extent, stimulate it. Depending on the implementing actor, environmental regulations are divided into formal and informal types [49]. Formal environmental regulations include command-and-control and market-incentive approaches, while informal environmental regulations primarily involve voluntary public participation. Command-and-control environmental regulation (CER) refers to the government imposing mandatory constraints on pollutant emissions and other behaviors of innovation stakeholders based on relevant laws and standards, and forcing innovation stakeholders to shift towards green innovation development by clarifying behavioral boundaries and responsibility requirements [48]. Market-based environmental regulation (MER) refers to using market price signals and economic incentives to guide innovation actors to choose green behaviors autonomously and to optimize resource allocation to the maximum extent while meeting green requirements, thereby promoting green innovation [50]. Public Participation Environmental Regulation (PER) uses diverse means, such as information disclosure, social oversight, and public pressure, to help enterprises and the public develop green awareness, thereby promoting green innovation [51]. Therefore, this study argues that, at the environmental layer of the green innovation ecosystem, these

three types of ecological regulation promote green innovation activities by constraining the behavior of innovation actors and guiding the direction of green innovation.

The green innovation environmental layer enhances ER mainly through the following three aspects. First, the core role of CER is to strengthen the sustainability of the energy system through structural reshaping and behavioral constraints. Command-and-control policies can promote structural adjustments in high-energy-consuming and high-emission industries, thereby enhancing the energy system's resilience to external disturbances [52]. CER, through routine supervision and inspection and penalties for violations, standardizes enterprises' daily energy use and environmental compliance, preventing the accumulation of risks driven by short-term interests, thereby improving the sustainability of the energy system [53]. Second, MER, with market mechanisms at its core, can significantly alter enterprises' production decision-making logic and resource allocation behavior through a range of tools, including carbon emission trading, green subsidies, and environmental taxes. Driven by both emission-reduction pressure and profit, enterprises shift towards investing in energy-saving renovations, fuel substitution, or carbon capture technologies, thereby reducing carbon intensity and energy consumption per unit of output [54], thereby improving the overall robustness of the energy system. Third, PER, characterized by public oversight and governance, can enhance the energy system's ability to cope with complex disturbances from two dimensions: the regulatory system and public acceptance. On the one hand, the public, as an essential supplement to administrative oversight, can effectively compensate for the inadequacy of administrative regulatory resources due to their widespread distribution [55], promoting a more efficient and adaptable regulatory system in the energy market. On the other hand, public preferences for green energy are directly transmitted through market choices and consumption behavior. When consumers are more inclined to choose green electricity products, energy-saving appliances, or support clean energy projects such as distributed photovoltaics [56], this signal will guide energy companies to increase the supply of clean energy and optimize energy services, thereby driving the green transformation of the energy system from production to consumption.

2.3. Green Innovation Supporting Layer and ER

The development of innovation capabilities in a green innovation ecosystem depends on long-term investment in key resources. Green finance (GF) guides capital from energy-demanding industries into green industries through a series of innovative financial products [57], providing crucial financial support for green innovation. Furthermore, digital infrastructure (DI) builds information platforms via digital networks [58], accelerating the flow of innovation elements and providing technical support for the innovation activities of diverse stakeholders in the green innovation ecosystem. Within the supporting layer of the green innovation ecosystem, GF and DI jointly provide the auxiliary resources of capital and technology for green innovation.

The green innovation supporting layer contributes to ER through two primary channels. First, GF plays a guiding and allocative role in funding, providing crucial support for energy transition and energy efficiency improvement. On the one hand, GF can reduce the energy system's reliance on traditional fossil fuels and accelerate the transition of the overall energy system toward cleaner, lower-carbon energy by supporting renewable energy projects, including hydropower, wind power, and solar power [59,60]. On the other hand, the targeted support for technological research and development provided by GF facilitates improvements in the operational efficiency and resilience of existing energy infrastructure. Second, DI can improve the operational efficiency of energy production, transport, and consumption. For instance, blockchain-based energy trading platforms can achieve real-time synchronization in energy exchanges [61], facilitating the development

of energy management in an industrial symbiosis network for safety, transparency, and automation, thus enhancing overall efficiency, enhancing the energy system's adaptability to supply-demand fluctuations, and reducing the risk of systemic instability.

2.4. Configuration Analysis Framework

Based on the theory of green innovation ecosystems, this study analyzes the pathways to improve ER and the interrelationships among the core, environmental, and supporting layers of green innovation. In the green innovation ecosystem, diverse innovation actors such as enterprises, universities, research institutions, governments, and the public can achieve multi-level interactions through collaborative interaction with the innovation environment and resources, thereby supporting the improvement of ER. There are dual cooperation and multi-level collaboration relationships among the three layers. First, green technology achievements provide feasibility support for the formulation of environmental regulatory standards. In contrast, environmental regulatory standards can drive actors to pursue green innovation, thereby forming cross-layer interactions between the core and environmental layers. Second, information sharing among innovation actors highly relies on digital infrastructure [62], which removes the physical and spatial limitations of innovation activities. Distributed innovation strengthens professional division of labor and collaboration, improves the efficiency of R&D innovation activities, significantly reduces the risks and costs, and strengthens the support capacity of the supporting layer for the core layer's innovation activities. Finally, environmental regulations, by providing policy guidance and setting institutional constraints, enable green finance to more effectively support green innovation, forming an interaction among the core, environmental, and supporting layers. The complex interconnections among the three levels enable them to improve ER synergistically.

In summary, based on the above analysis, this study presents Figure 1, which selects seven variables, namely RGI, IGI, CER, MER, PER, GF, and DI, under the three dimensions of the green innovation core layer, green innovation environment layer, and green innovation supporting layer. Through complex synergistic mechanisms, these variables form multiple pathway combinations that influence the improvement of regional energy resilience.

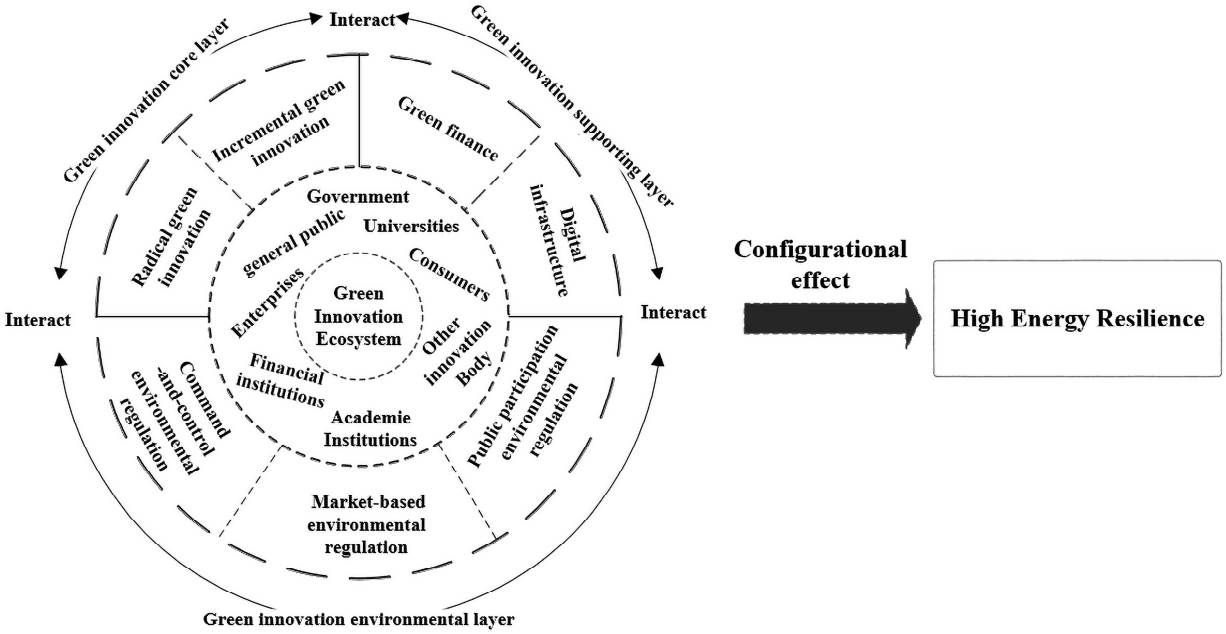


Figure 1. Logical framework of the impact of the green innovation ecosystem on ER.

3. Research Design

3.1. Research Method

This study employs the dynamic QCA method for the following reasons. First, the QCA method explores the impact of combinations of multiple condition variables on the outcome. This method overcomes the limitations of net-effect-based causal reasoning [37]. It compensates for the shortcomings of traditional regression methods, which can analyze only the net effect of a single variable on the outcome variable. This method is well-suited to the study's research objectives. Second, the QCA method applies to both small-to-medium samples (10–50 cases) and large samples exceeding 100 cases [63]. This study uses 30 provinces in China as its research sample, with a sample size consistent with the method. Third, since no condition variable in this study can be considered binary, and the QCA method can effectively address variable ambiguity through set membership calibration, it fits the variable characteristics of this study. Finally, the dynamic QCA method, by integrating indicators such as Pooled Consistency (POCONS), between-group consistency differences (BECONS), within-group consistency differences (WICONS), Pooled Coverage (POCOV), between-group coverage differences (BECOV), and within-group coverage differences (WICOV) [64], can simultaneously analyze changes in conditional configurations among different cases, as well as the trajectory of changes in the same case at various time points. By leveraging the consistency-adjustment distance metric, dynamic QCA can also capture subtle changes in configuration over time and space. Therefore, the dynamic QCA method not only accurately adapts to the sample size and variable characteristics of this study but also specifically addresses the three core issues raised, thereby ensuring alignment between the methodological choice and the research objectives.

3.2. Research Samples and Data Collection

Following the principles of data availability and comparability, this study excluded regions with significant differences in statistical scope or severe data gaps, ultimately selecting 30 provincial-level administrative areas in mainland China. The research sample covers the period from 2016 to 2022. The choice of this research period is significant: since 2016, the government has introduced policies across science and technology, energy, and finance, providing ample institutional background for the research. Second, the accelerated green transformation of industries and economic restructuring across regions help capture differences in ER enhancement; furthermore, the COVID-19 pandemic in 2020, as an exogenous shock, provided a natural experimental context for comparing the risk-resistance capabilities of energy systems across regions.

The data mainly comes from the following two parts: (1) Data on the green innovation ecosystem. The dual green innovation data comes from the China Research Data Service Platform (CNRDS); the environmental regulation data is obtained by sorting out the policy documents published on the official websites of the Ministry of Ecology and Environment and the Ministry of Natural Resources. The GF data is comprehensively sourced from the China Science and Technology Statistical Yearbook, China Financial Statistical Yearbook, China Agricultural Statistical Yearbook, China Industrial Statistical Yearbook, and China Tertiary Industry Statistical Yearbook. The DI data is sorted and extracted from provincial government work reports. (2) Data on ER. This part of the data mainly comes from authoritative institutions such as the National Bureau of Statistics and the National Energy Administration, as well as official statistical yearbooks, including the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Environmental Statistical Yearbook, and the Statistical Communiqué on National Economic and Social Development. For a small number of missing values, this study uses linear interpolation to supplement them, ensuring data completeness and the reliability of the empirical analysis.

3.3. Variable Description

3.3.1. Conditional Variables

- Green patents serve as direct evidence of enterprises' or research institutions' innovative achievements in green technology, characterized by their environmental attributes. Therefore, this study, drawing on the examples of Wang and Sun, uses the number of green inventions and green utility model patents to measure RGI and IGI, respectively [65].
- The number of local environmental regulations and environmental administrative penalty cases reflects the policy supply and the strength of government-mandated supervision. Drawing on Xie et al. [48] and Wang et al. [66], This study uses these two indicators to measure CER. The core of MER is to leverage market mechanisms to exert both constraints and incentives. This study, drawing on the approach of Li and Ramanathan [67], selects two indicators—investment in industrial pollution control and the environmental protection tax—to measure this. Following the approach of Yang et al., the number of environmental protection-related proposals submitted by each province to the National People's Congress and the Chinese People's Political Consultative Conference is used to measure PER. These two indicators effectively reflect the actual degree of public participation in environmental governance [68]. Each sub-indicator was objectively weighted and comprehensively fitted using the entropy weight method to obtain the combined values of CER, MER, and PER.
- Green credit, green investment, green insurance, green bonds, green subsidies, green funds, and green equity reflect the functions and roles of GF from different perspectives. Therefore, this study, drawing on the approach of Shang et al., employs the entropy weight method to calculate the GF Index [69] using these seven dimensions as indicators. Based on the original word-frequency data for 51 DI-related terms such as 5G, mobile communication, and information technology in provincial policy documents, the total word frequency is used to measure DI levels across provinces. Details of the condition-variable indicators are shown in Table 1.

Table 1. Indicator system of conditional variables.

Indicators	Secondary Indicators	Calculations	Direction
RGI	Green invention patent authorizations	Number of authorized green invention patents (pieces)	+
IGI	Green utility model patent authorizations	Number of authorized green utility model patents (pieces)	+
CER	Local environmental regulations	Number of effective local environmental protection regulations (items)	+
	Environmental administrative penalty cases	Number of environmental administrative penalty cases	+
MER	Industrial pollution control investment	Investment in industrial pollution control (million CNY)	+
	Environmental protection tax	Environmental protection tax revenue (million CNY)	+
PER	Environmental protection proposals (NPC)	Number of environmental protection-related proposals submitted to the NPC (pieces)	+
	Environmental protection proposals (CPPCC)	Number of environmental protection-related proposals submitted to the CPPCC (pieces)	+
GF	Green credit	Green credit / total credit (%)	+
	Green Investment	Environmental pollution control investment / GDP (%)	+
	Green Insurance	Environmental pollution liability insurance revenue / total premium revenue (%)	+
	Green bonds	Green bond issuance/total bond issuance (%)	+
	Green support	Fiscal expenditure on environmental protection / total fiscal spending (%)	+
	Green funds	Market capitalization of green funds/total fund market capitalization (%)	+
	Green equity	Trading volume of carbon, energy use, and emission rights/equity market (%)	+
DI	Total frequency of related keywords	Total annual word frequency of DI-related keywords in provincial policy documents (times)	+

3.3.2. Outcome Variables

Based on the research of Sharifi and Yamagata, this study measures ER from four dimensions: resistance, absorptive capacity, recovery capacity, and adaptive capacity [70], and constructs a multidimensional indicator system, as shown in Table 2.

Table 2. ER indicator system.

Indicators	Secondary Indicators	Tertiary Indicators	Calculations	Direction
Energy Resilience	Resistance	Low-carbon level of energy consumption structure (%)	Index of the low-carbon level of energy consumption structure	–
		Energy consumption per unit of GDP (tons/10,000 RMB)	Total energy consumption/GDP	–
	Absorptive Capacity	Renewable energy power consumption (100 million kWh)	Actual renewable electricity consumption	+
		Contribution rate of the tertiary industry (%)	Increment of tertiary industry/Increment of GDP	+
		Length of natural gas pipelines (km)	Total length of natural gas pipelines	+
	Recovery Capacity	Comprehensive utilization rate of industrial solid waste (%)	Amount of comprehensively utilized general industrial solid waste/Total amount of generated general industrial solid waste	+
		Per capita sulfur dioxide emissions (tons/person)	Total sulfur dioxide emissions/Total population	–
	Adaptive Capacity	Direct economic losses from natural disasters (billion RMB)	Direct economic losses caused by natural disasters	–
		Proportion of fixed asset investment in the energy industry (%)	State-owned fixed asset investment in the energy industry/Total social fixed asset investment	+
		Forest coverage rate (%)	Forest area / Total land area	+
		Per capita energy consumption (tons/person)	Total energy consumption/Total population	–
		Industrial output per unit of GDP (%)	Industrial output value/GDP	+

- Resistance refers to an energy system's ability to withstand shocks in the early stages of a disturbance. Enhancing this capacity involves two main aspects: first, reducing the economy's dependence on energy consumption by improving energy efficiency; and second, reducing the proportion of volatile fossil fuels by promoting a cleaner energy structure. Therefore, this study selects energy consumption per unit of GDP and the low-carbonization level of the energy consumption structure to measure resistance [71].
- Absorptive capacity refers to the energy system's ability to buffer against negative impacts after a shock occurs. The energy structure's absorbability, the economic structure's diversity, and the interconnection of the transmission and distribution networks jointly determine the energy system's shock-bearing capacity. The energy system's ability to absorb clean energy, especially volatile energy, is an important component of its shock absorption. Industrial diversification can weaken the transmission of risks from a single sector, and a well-developed pipeline network can enhance the flexibility of energy dispatch. Therefore, this study selects three indicators to measure absorptive capacity: renewable energy power consumption, the tertiary industry's contribution rate, and natural gas pipeline length [13,16].
- Recovery capacity refers to an energy system's ability to restore its function and operational efficiency after damage. Good resource recycling, robust environmental governance, and lower disaster losses can shorten the recovery cycle and reduce reconstruction costs, which are essential aspects of measuring the system's recovery capacity. Therefore, three indicators were selected to measure recovery capacity, namely the comprehensive utilization rate of industrial solid waste, per capita sulfur dioxide emissions, and natural disaster losses [16].

- Adaptive capacity refers to an energy system's ability to perform structural optimization and innovation based on experience and learning after experiencing shocks, making it more flexible in responding to future disruptions [70]. This ability depends on three key aspects: capital investment to provide impetus for infrastructure upgrades, technological research, and development. Resource allocation efficiency can optimize the relationship between energy utilization and economic output. The ecological environment provides buffer space and resource support for long-term system adjustments. Therefore, four indicators were selected to measure adaptive capacity, namely the proportion of fixed asset investment in the energy industry, per capita energy consumption, industrial output per unit of GDP, and forest coverage rate [17].

3.3.3. Indicator Processing and Index Aggregation

To ensure the objectivity and comparability of the CER, MER, PER, GF, and ER indicator systems, this study uniformly adopts the entropy weight method for weight determination and index aggregation. Indicator processing based on the Entropy Weight Method and comprehensive index construction follows these steps [72].

(1) Indicator homogenization. For positive indicators, the original data characteristics are retained. For negative indicators, a Linear Reverse Method is used to transform them into positive indicators, ensuring that all indicators have the same evaluation direction.

(2) Normalization. The Min-Max Normalization Method is used to normalize the indicators, mapping the values to the [0, 1] interval to eliminate differences in dimensions and orders of magnitude.

(3) Entropy weight calculation. The probability distribution of the normalized values of the indicators is calculated, the information entropy is obtained, the difference coefficient is derived, and the weights are determined according to their proportions.

(4) Weight summation. The normalized values are weighted and summed with their corresponding weights to form the comprehensive scores of indicators such as CER, MER, PER, GF, and ER. This provides basic data for subsequent analysis.

3.4. Data Calibration

Following the approach proposed by FISS [73], this study employs a direct calibration method. Drawing on the work of Ragin, C.C., and Schneider, C.Q., and based on the distribution of variables in the sample, 95%, 50%, and 5% of the sample were set as calibration anchors for Full membership, the crossover point, and Full non-membership, respectively [74,75]. This anchor setting is well-suited to the distribution characteristics of the sample compared with alternative calibration methods. All data were calibrated to fuzzy sets ranging from 0 to 1 accordingly. To avoid cases being excluded from the analysis when the fuzzy set membership degree is exactly 0.5, following the approach of Campbell et al. and Mattke et al. [74], the membership degree of 0.5 was replaced with 0.501. The descriptive statistics indicate that the variables exhibit appropriate distributions, providing a sound basis for fuzzy-set calibration and subsequent configurational analysis. The specific calibration anchor points and descriptive statistical results are shown in Table 3.

Table 3. Calibration anchors of variables.

		Calibration			Descriptive Statistics			
		Full Non-Membership	**Crossover Point**	**Full Membership**	**Mean**	**Std.Dev.**	**Min**	**Max**
Outcome variable	ER	0.244	0.324	0.338	0.338	0.070	0.211	0.560
Conditional variables	RGI	270.150	2496.000	4627.286	4627.286	5792.033	125.000	25,420.000
	IGI	420.050	2864.000	4987.238	4987.238	6122.283	116.000	35,358.000
	CER	0.017	0.089	0.135	0.135	0.128	0.011	0.726
	MER	0.012	0.106	0.149	0.149	0.139	0.004	0.700
	PER	0.021	0.165	0.192	0.192	0.150	0.00024	0.716
	GF	0.111	0.407	0.347	0.347	0.130	0.097	0.632
	DI	8.000	18.000	18.167	0.347	6.619	5.000	39.000

4. Results

4.1. Necessity Analysis of Single Conditions

The purpose of necessity analysis lies in determining whether there exists an individual conditional variable that leads to the outcome variable. A conditional variable is identified as a necessary condition for the outcome if its consistency exceeds 0.9. In dynamic QCA, further judgment is needed by considering the between-group consistency adjusted distance. When it is lower, stability is greater; when the adjusted distance surpasses 0.2, it is necessary to further examine the necessity of the condition.

Table 4 presents the necessity of the seven conditional variables. Each conditional variable's consistency level is below 0.9, which indicates that none of them qualify as a necessary condition. Moreover, an in-depth analysis was carried out on the causal condition combinations in which the consistency adjusted distance lies above 0.2, and the relevant results are displayed in Table 5. The findings demonstrate that, for these combinations, consistency does not reach 0.9. Therefore, no necessary relationship exists.

Table 4. Results of necessary condition analysis.

Condition Variable	**High ER**			
	Pooled Consistency	**Pooled Coverage**	**Between-Group Consistency Adjusted Distance**	**Within-Group Consistency Adjusted Distance**
RGI	0.725	0.839	0.077	0.443
~RGI	0.656	0.542	0.067	0.408
IGI	0.741	0.843	0.103	0.420
~IGI	0.651	0.544	0.099	0.403
CER	0.691	0.732	0.196	0.454
~CER	0.653	0.578	0.144	0.414
MER	0.708	0.75	0.135	0.362
~MER	0.672	0.594	0.045	0.397
PER	0.787	0.815	0.096	0.408
~PER	0.547	0.493	0.189	0.518
GF	0.705	0.685	0.077	0.466
~GF	0.612	0.585	0.279	0.460
DI	0.681	0.686	0.186	0.282
~DI	0.652	0.603	0.176	0.345

Table 5. The data on the between-group consistency-adjusted distance is greater than 0.2.

Causal Combination Situation		2016	2017	2018	2019	2020	2021	2022
~GF and ER	consistency	0.840	0.788	0.713	0.621	0.545	0.467	0.439
	coverage	0.543	0.535	0.557	0.595	0.606	0.614	0.71

4.2. Sufficiency Analysis of Conditional Groupings

This study uses the R language (version 4.4.2) and the SetMethods (version 4.0) and QCA (2.1.0) software packages to conduct dynamic QCA. The parameter setting process comprehensively considers literature recommendations and data characteristics. Specifically, first, given a total sample of 210 cases, we need to ensure at least 75% are retained to guarantee the validity of the analysis. In this study, the sample frequency threshold was set to 2, yielding 182 observed samples in the truth table, exceeding 75% of the total sample size. Second, referring to the minimum acceptable threshold proposed by FISS et al. [73] Given the distribution of consistency scores in this study, the original consistency threshold is set to 0.9. Third, to avoid specific configurations having subset relationships simultaneously under the negation of solutions, the PRI consistency threshold must be at least 0.5 [76]. Therefore, this study adopted a strict standard of 0.8 to strengthen the rigor of causal inference and pathway differentiation. Furthermore, since existing research has not reached a consistent conclusion regarding the impact of various antecedent conditions on ER, and given the strong imbalance in regional development, the direction of the effect of antecedent conditions on the outcome should not be judged using a unified standard [77]. Therefore, adhering to the principle of prudence in the counterfactual analysis section, no directional setting of antecedent conditions was made. Simultaneously, three solutions were generated using standard analysis: a complex solution (excluding logical remainders), an intermediate solution (containing some logical remainders), and a parsimonious solution (containing all logical remainders) [78]. The configuration result was ultimately determined by analyzing the nesting relationship between the intermediate and parsimonious solutions.

4.3. Configuration Analyses

Table 6 identified three pathways, all with consistency coefficients exceeding 0.9, indicating that H1 (H1a, H1b, H1c), H2, and H3 were all sufficient conditions for achieving high ER. Among them, configurations H1a, H1b, and H1c shared the same core variable, representing second-order equivalent configurations. The overall solution coverage across the three configurations was 0.551, which can explain 55.1% of cases. Detailed analysis follows.

4.3.1. Green Finance-Enabled Configuration

The H1 pathway comprised three sub-pathways—H1a, H1b, and H1c—with consistency levels of 0.970, 0.976, and 0.976, respectively, explaining 36.8%, 30.8%, and 41.9% of the cases. The H1 pathway has four core conditions: RGI, IGI, PER, and GF. Under this framework, the improvement of ER primarily relies on the synergistic effect of dual green innovation driving force, social supervision, and financial support. Specifically, when a regional energy system faces external shocks, PER can promote the optimization of existing technologies by constraining corporate behavior; simultaneously, it transmits public environmental demands to universities and research institutions, guiding them to conduct targeted research and drive technological breakthroughs, forming a technology feedback mechanism and promoting the realization of IGI. GF provides both the R&D funding needed for RGI to bear high risks and the capital guarantee for the large-scale application of IGI. CER and MER play only marginal or substitutable roles in this configu-

ration. In H1a, the two types of environmental regulations are conditions that may or may not exist. In H1b, they are marginal and absent. In H1c, they exist as a peripheral causal condition. This demonstrates that even if some non-core conditions are insufficient, the strong synergistic effect of core conditions can still support improved ER. Furthermore, when both core and peripheral conditions play a strong role simultaneously, a synergistic amplification effect can be generated, as illustrated in Figure 2.

Table 6. Configurations for achieving high ER.

Conditional Variable	Configuration Analysis—High ER				
	H1a	**H1b**	**H1c**	**H2**	**H3**
RGI	●	●	●	●	•
IGI	●	●	●	•	•
CER		⊗	•	⊗	●
MER		⊗	•	●	⊗
PER	●	●	●	•	●
GF	●	●	●	⊗	⊗
DI	⊗				●
Consistency	0.970	0.976	0.976	0.976	0.975
PRI	0.904	0.891	0.937	0.862	0.866
coverage	0.368	0.308	0.419	0.271	0.253
Unique coverage	0.014	0.021	0.069	0.015	0.012
BECONS-adjusted distances	0.026	0.019	0.016	0.022	0.013
WICONS-adjusted distances	0.109	0.104	0.104	0.098	0.098
POCONS			0.974		
Pooled PRI			0.938		
POCOVS			0.551		

Note: ● = core causal condition (present); ⊗ = core causal condition (absent); • = peripheral causal condition (present); ⊗ = peripheral causal condition (absent); blank spaces indicate "do not care".

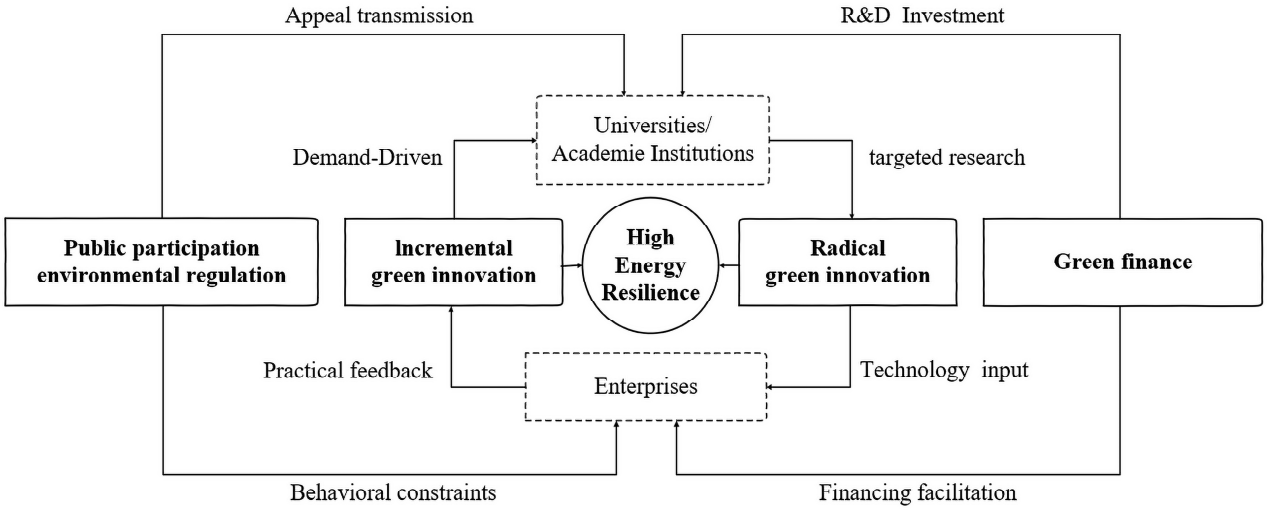


Figure 2. Green finance-enabled configuration.

Jiangsu Province is a typical example of this pathway. From 2019 to 2022, Jiangsu Province's ER membership value was above 0.85, while the membership values of RGI, IGI, PER, and GF generally remained around 0.80. The province has improved its GF support system, providing multi-level financial guarantees for green innovation actors. On the one hand, banks have launched dedicated credit products for low-carbon projects, providing risk capital support for RGI and helping to overcome technological challenges in hydrogen

energy, energy storage, and photovoltaics. On the other hand, it promotes large-scale IGI adoption through green bonds and industrial funds, accelerating the green transformation of traditional manufacturing industries. Furthermore, Jiangsu Province has strengthened public participation and social supervision, thereby fostering effective interaction with market mechanisms and further consolidating improvements in ER.

4.3.2. Market Incentive-Driven Configuration

The consistency level of pathway H2 is 0.976, and the coverage is 27.1%. The core conditions of this pathway, RGI and MER, indicate that improving ER primarily relies on the synergistic effect of breakthroughs in cutting-edge technologies and market incentives. This suggests that improved ER mainly depends on the synergistic impact of breakthroughs in cutting-edge technologies and market incentives. In this configuration, even with insufficient GF support, companies can still access innovation resources through other channels when market incentives are sufficient. Specifically, on the one hand, MER, through policy guidance on energy structure optimization and profit-driven industrial upgrading, sends clear market signals to companies for energy transition. These signals can attract conventional commercial capital to the field of green energy innovation. On the other hand, PER compels companies to consider environmental responsibility in their routine commercial capital operations, thereby obtaining premium returns by building a good social reputation and thus enhancing long-term returns. The dual effects of investment signal guidance and the reputation premium ensure that conventional commercial capital remains a vital financing channel for green energy innovation even in the absence of GF. Notably, the dominance of RGI suggests that in the absence of mandatory regulations and sufficient financial support, technological breakthroughs are more effective than technological improvements in significantly enhancing the resilience of the energy system. This may be because radical innovation often leads to paradigm shifts and drives the formation of new technologies, as illustrated in Figure 3.

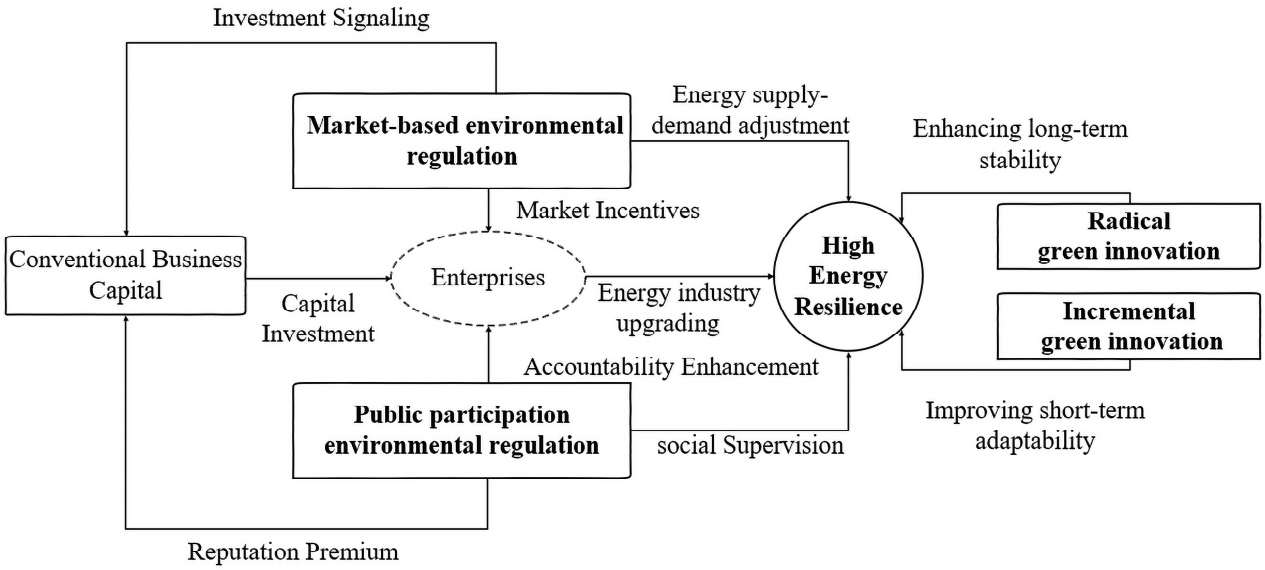


Figure 3. Market incentive-driven configuration.

Hubei and Henan provinces are typical examples of this pathway. In 2016, Hubei Province had MER and PER membership values of 0.7 and 0.99, respectively, while in 2022, Henan Province had MER and PER membership values of 0.56 and 0.95, respectively. However, the GF membership values were relatively low, at 0.47 and 0.35, respectively, exhibiting a typical combination of market incentives and social supervision-driven growth, but insufficient financial support. Hubei Province, leveraging science and technology inno-

vation platforms such as the Wuhan East Lake High-tech Development Zone, promotes breakthroughs in new energy technologies and guides enterprises to reduce emissions through incentive policies, including carbon trading markets and green credit. Simultaneously, PER strengthens social supervision. For example, the "Yangtze River Protection" campaign, combined with environmental information disclosure, attracts commercial capital to clean energy projects. Henan Province promotes the "relocation from urban areas to suburbs" project in cities such as Pingdingshan and Jiaozuo, transforming coal mine sites that have been removed from urban areas into distributed photovoltaic + energy storage demonstration bases, while simultaneously constructing underground compressed air energy storage projects, achieving the secondary development of mining land resources.

4.3.3. Digital Infrastructure-Supported Configuration

The consistency level of pathway H3 was 0.975, and the coverage was 25.3%. This configuration is based on CER, PER, and DI as core conditions, with dual green innovation as a supplementary condition. In the absence of market incentives and GF support, improved ER can be achieved through mandatory policy constraints, social supervision, and digital support. CER directly restricts high-carbon behavior through mandatory standards, encouraging companies to eliminate outdated production capacity and engage in green innovation. PER compensates for the limitations of government regulation through social supervision. DI plays a core supporting role in this configuration. On the one hand, by collecting and monitoring corporate emissions data in real time, CER shifts from outcome-based punishment to process control; on the other hand, by relying on energy big data platforms to publicly disclose environmental performance, the threshold for public supervision is lowered, and the coverage of social supervision is expanded. Simultaneously, DI supports the coordinated operation of dual green innovation through intelligent monitoring and information sharing, and enhances overall resilience by strengthening the efficiency and stability of the energy system, as illustrated in Figure 4.

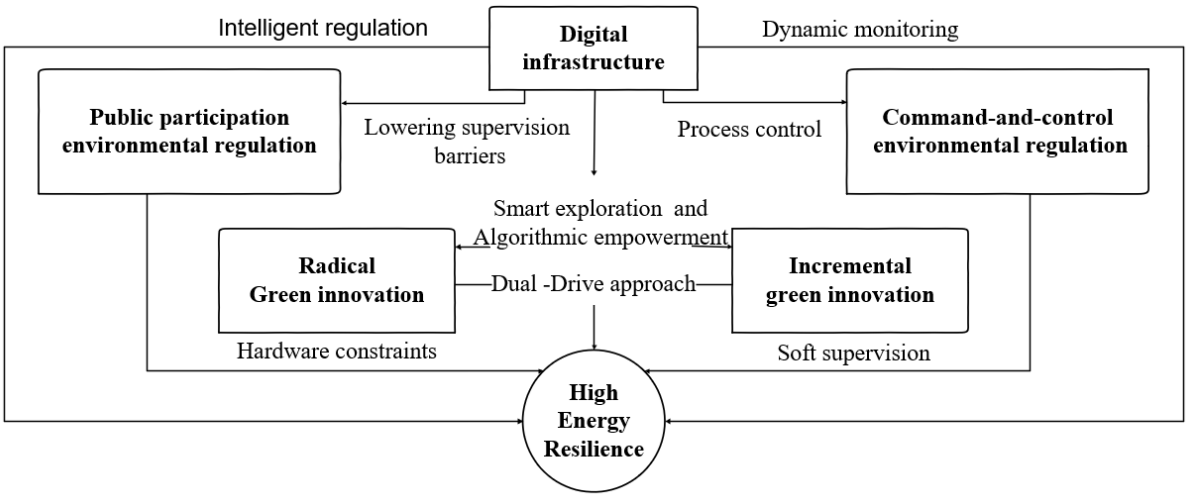


Figure 4. Digital infrastructure-supported configuration.

Sichuan Province is a typical case of this pathway. In 2022, Sichuan Province's ER membership value was 0.98, and its CER, PER, and DI were 0.52, 0.89, and 0.62, respectively. The province has enforced the closure of high-energy-consuming and high-polluting enterprises, eliminated outdated production capacity, and encouraged enterprises to improve traditional energy utilization technologies and explore new energy applications. Simultaneously, Sichuan Province has established an "Environmental Credit Evaluation System," publicly disclosing enterprise pollution emission data and encouraging public participation

in supervision through an environmental whistleblowing platform. The provincial-level energy big data center, built upon the "Tianfu Cloud" platform, enables real-time monitoring of carbon emissions from key enterprises and grid load, effectively improving the precision of regional energy system supervision and operational efficiency.

4.4. Between-Group Analysis

To further examine how each configuration pathway evolves over time, this study presents a consistency trend chart between groups (Figure 5).

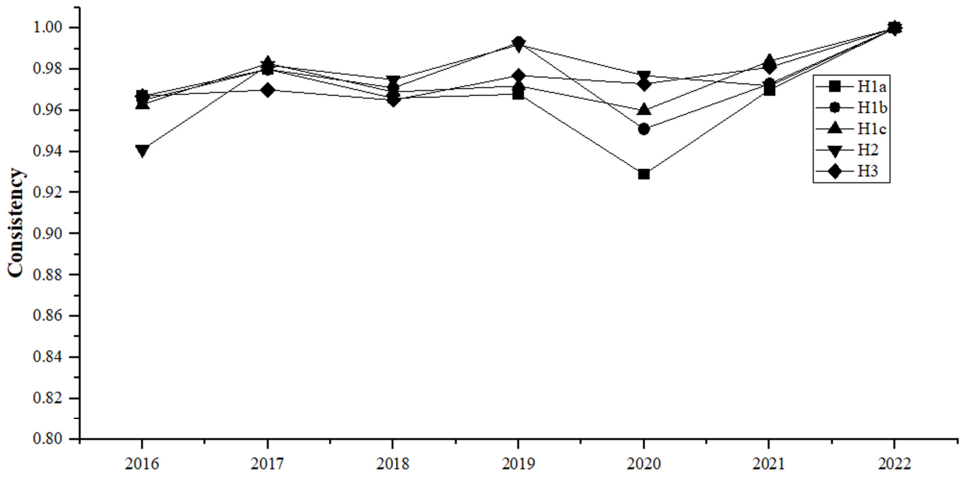


Figure 5. Changes in between-group consistency levels.

As shown in Figure 5, the consistency among all configuration groups reached above 0.90, significantly higher than the 0.75 threshold, and all adjustment distances were less than 0.2. This indicates that there is no significant time effect, the three pathways are structurally stable over time, and the explanatory power of each configuration for achieving high ER is relatively consistent across different years. Further analysis reveals that the consistency level of all configurations fluctuated between 0.92 and 1 from 2016 to 2022, remaining stable over time. Specifically, the initial value of configuration H2 in 2016 was low, possibly due to the fact that the national carbon market was not yet mature at that time, and that carbon market regulation faced challenges. During 2016–2017, the full implementation of the 13th Five-Year Plan led to the gradual implementation of relevant energy policies, resulting in a slight increase in consistency across all configurations. In 2018, all configurations experienced a slight decline, a fluctuation possibly related to macroeconomic uncertainties, such as Sino-US trade frictions. In 2020, the consistency values for all configurations showed a significant decrease. This may be due to the COVID-19 pandemic, which restricted personnel movement, disrupted supply chains, and delayed cash flow, leading to insufficient innovation vitality among green innovation actors, weakened regulatory enforcement, and delayed factor supply response. However, pathway H3, centered on DI, experienced less fluctuation during this period, demonstrating strong stability. This indicates that this pathway exhibits strong stability in responding to sudden external shocks by ensuring information flow and strengthening processes. Managing and enhancing innovation efficiency provides a reliable means to improve ER. Nevertheless, since the inter-group consistency distance remains less than 0.2, it does not affect the overall explanatory power of the configurations. The three configurations have a certain degree of universality and can provide a reference for improving ER. Furthermore, all pathways began to converge in 2021, reaching a high point in 2022. This indicates that the green innovation ecosystem is increasingly important in improving ER. This is because China's "14th Five-Year Plan" comprehensively promotes the energy revolution and constructs

a modern energy system. The "14th Five-Year Plan" for a modern energy system, issued by China in 2022, provides comprehensive strategic guidance for local energy development, thereby maximizing the explanatory power of each configuration.

4.5. Within-Group Analysis

Although this study proposes three pathways, namely green finance-enabled, market-incentive driven, and digital infrastructure-supported, that have played a positive role in enhancing ER, the effectiveness of each pathway varies significantly across regions due to differences in innovation foundations, resource endowments, and policy environments.

In terms of regional coverage (Table 7), the green finance-enabled pathway explains the highest coverage of cases in the central region, followed by the eastern region. The eastern region is primarily represented by provinces such as Shandong (2017–2022), Zhejiang (2017–2022), Guangdong (2016–2022), Fujian (2017, 2021, 2022), and Hebei (2017, 2021, 2022). The central region is mainly represented by Hubei (2017, 2018, 2021, 2022) and Hunan (2019, 2020, 2021, 2022). Compared to western regions, eastern and central regions demonstrate stronger capabilities in perceiving environmental changes and seizing emerging opportunities, enabling them to respond swiftly to shifts in policy, market dynamics, and technology. Simultaneously, as basic material needs are met, the public has developed heightened expectations for environmental quality. Against this backdrop, PER, through strengthened social supervision and policy guidance, effectively channels capital toward green projects that combine economic and environmental benefits. This drives innovation actors to prioritize green innovation as a core strategy and incentivizes enterprises to increase R&D in areas such as clean energy, energy efficiency improvement, and the circular economy, thus enhancing the diversification of the energy supply structure.

Table 7. Regional coverage averages.

Regions	H1	H2	H3
Eastern Region	0.427	0.201	0.179
Central Region	0.470	0.463	0.484
Western Region	0.261	0.280	0.249

Case studies explaining market incentive-driven pathway are mainly concentrated in the central region, with Henan (2022) and Hubei (2016) as typical representative provinces. The central region has a high proportion of secondary industry, and its energy system is dominated by traditional energy sources, resulting in an urgent need for green transformation. Consequently, local governments generally promote carbon emission trading systems and pollution discharge rights trading systems, incorporating environmental factors into a market-based allocation framework, transforming enterprises' energy conservation and emission reduction behaviors from passive compliance to a quantifiable asset accumulation process. When every unit of energy saved or every unit of emission reduced can be traded and monetized in the market, enterprises gain sustained incentives and are more willing to invest in high-cost but long-term-return green technology R&D and transformation projects, thereby promoting the optimization of the energy system structure.

Case studies explaining the digital infrastructure-supported pathway are relatively few, mainly distributed in the central and western regions, with Sichuan (2022) and Anhui (2021) as typical representative provinces. Although the central and western regions have relatively abundant hydropower and clean energy resources, their energy system operation faces challenges such as complex terrain conditions and difficulties in cross-regional power transmission. Against this backdrop, by strengthening the construction of DI, relying on the wide-area Internet of Things to break geographical limitations, and leveraging computing power advantages to optimize scheduling algorithms, an intelligent energy scheduling

system can be built to improve the overall efficiency and reliability of cross-regional power transmission. Furthermore, relying on the information disclosure mechanism of digital platforms, the entry threshold for social actors to participate in energy supervision can be lowered, the spatial and temporal scope of supervision coverage can be broadened, and a multi-governance pattern of government and social collaboration can be promoted. From a governance perspective, this ensures the stable operation and dynamic adaptation of the energy system, providing key support for improving the region's ER.

4.6. Confounding Variable Test

Regression analysis often controls for variables to mitigate sample heterogeneity. In QCA, confounding conditions play an analogous role. These conditions may exhibit latent causal relevance but do not constitute core explanatory factors. Generally speaking, confounding conditions can elucidate both the configurational characteristics that explain outcomes and reflect the nature of the outcomes themselves [79]. Researchers can employ theoretical and/or empirical approaches to identify critical "confounding conditions", categorize these conditions into "confounding conditions" and "non-confounding conditions" sets, and subsequently evaluate their logical redundancy. Calculate the proportion of "confounding conditions" to "non-confounding conditions" in each configuration. If the proportion of "confounding conditions" is significantly high or low, it indicates that there is a constant causal relationship among the confounding conditions in that configuration [80].

This study undertakes an analysis of whether the level of economic development constitutes a confounding variable. Calibration analysis of economic development levels revealed that among the 70 consistent cases selected for the solution set, 41 cases pertained to high economic development levels, while the remaining 29 cases corresponded to non-high economic development levels. The proportions of high and non-high economic development levels were calculated at 0.5857 and 0.4143 (Table 8), respectively. This indicates that, at the solution level, the proportion of regions with non-high economic development is relatively small, implying logical redundancy. This suggests that regardless of whether economic development is high or low, it does not interfere with the overall causal mechanism. However, more noteworthy is the individual configuration pattern. The proportions of regions with non-high economic development corresponding to configurations H1, H2, and H3 are 48.48%, 31.43%, and 100%, respectively. The product of confounding and non-confounding case ratios yields a maximum value of 0.25 (0.50×0.50) and a minimum of 0.00 (0.00×1.00). Dividing this product by 0.25 (the maximum) yields a heterogeneity value ranging from 1.00 to 0.00. The heterogeneity coefficients for the three pathways are 0.9992, 0.8620, and 0.0000, respectively. This indicates that the level of economic development exhibits logical redundancy (with heterogeneity approaching 1) in both the H1 and H2 pathways, implying that variations in economic levels do not affect the configurational outcomes. The heterogeneity of the H3 pathway is 0, which may be attributed to contingency bias due to an extremely small sample size; nevertheless, this does not undermine the overall conclusion.

Table 8. Confounder condition.

Configuration	High Economic Development		Low Economic Development		Heterogeneity
	Number	Participation	Number	Participation	
H1	17	0.5152	16	0.4848	$(0.5152 \times 0.4848) \div 0.25 \approx 0.9992$
H2	24	0.6857	11	0.3143	$(0.6857 \times 0.3143) \div 0.25 \approx 0.8620$
H3	0	0	2	100	$(0.0000 \times 1.0000) \div 0.25 = 0.0000$
Total	41	0.5857	29	0.4143	$(0.5857 \times 0.4143) \div 0.25 \approx 0.9706$

4.7. Robustness Analysis

To verify the robustness of the combination of conditional variables in achieving high ER, this study analyzed two aspects: (1) Referring to the method of Oana and Schneider, a calibration sensitivity analysis was conducted [64,81]. The upper and lower bound anchor points of all variables are within a ±3% range. The robustness parameters (RF_cov, RF_cons, RF_SC_minTS, RF_SC_maxTS) after adjustment are all close to 1 (Table 9), indicating that small changes in the calibration anchor points do not affect the core conclusions, and the results are robust. (2) Referring to the method of Skaaning [82], with other conditions remaining unchanged, this study reduced the PRI consistency threshold from 0.8 to 0.75 and the original consistency threshold from 0.9 to 0.85, respectively. The conclusion of single-condition necessity did not change substantially, and the obtained solution pathway was basically consistent with the original configuration (Table 10), further demonstrating that the analysis results remain robust.

Table 9. Robustness Test of Calibration.

	RF_cov	RF_cons	RFSC_minTS	RFSC_maxTS
Change calibration anchor (92% 50% 8%)	0.947	0.95	0.885	0.885
Change calibration anchor (98% 50% 2%)	0.988	0.955	0.881	0.881

Table 10. Robustness test of configurations. Robustness Test of Calibration.

Conditional Variable	Robustness Test-1				Robustness Test-2			
	L1a	L1b	L2	L3	L4	M1	M2	M3
RGI	●	●	●	•	●	•	•	
IGI	●	●	•	•		•		
CER	•		⊗	•	⊗		⊗	•
MER	•		●		⊗			⊗
PER	●	●	⊗	•	●	•	•	•
GF	●	●		⊗	•	•	⊗	⊗
DI		⊗		•	●			
Consistency	0.976	0.970	0.976	0.942	0.972	0.977	0.969	0.954
PRI	0.937	0.904	0.862	0.762	0.849	0.947	0.841	0.800
coverage	0.419	0.368	0.271	0.293	0.289	0.519	0.300	0.306
Unique coverage	0.005	0.031	0.014	0.006	0.037	0.253	0.017	0.031
BECONS-adjusted distances	0.016	0.026	0.022	0.048	0.022	0.016	0.035	0.038
WICONS-adjusted distances	0.104	0.109	0.098	0.125	0.104	0.109	0.109	0.144
POCONS			0.956				0.962	
Pooled PRI			0.897				0.914	
POCOVS			0.571				0.609	

Note: ● = core causal condition (present); ⊗ = core causal condition (absent); • = peripheral causal condition (present); ⊗ = peripheral causal condition (absent); blank spaces indicate "do not care".

5. Discussion

First, the results of this study show that both dual green innovation and PER are present conditions in pathways H1, H2, and H3. From a necessity perspective, they are not indispensable elements for the outcome, but their widespread presence may suggest a synergistic effect in most successful pathways, making them essential conditions for improving ER. This finding aligns with Ruquan Lu's view [83], which indicates that the pursuit of innovative technologies has driven the development and application of numerous

energy technologies, including energy storage and microgrids. These technologies enhance the flexibility and diversity of energy systems while also improving their resilience under adverse conditions such as extreme weather. Research by Mu Xianzhong et al. also supports this point, proposing that when the public's personal qualities and environmental awareness reach a certain level and when individual interests align with overall social interests, this can positively impact corporate pollution behavior, thereby promoting growth in energy efficiency [84].

Second, research on factors influencing ER generally exhibits a "regional differentiation" characteristic [13,15,17,18,71]. Regarding regional classification, in addition to the geographical location-based classification standard used in this study, some scholars adopt economic development level and other classification criteria. In studies that also use geographically based classification standards, Rabindra Nepal et al.'s research [15] finds that GF has the most significant positive impact on ER in eastern regions. Perhaps due to the higher level of economic development and a more favorable environment for GF development in the eastern region, this corresponds with the conclusion drawn in this study that "the green finance-enabled pathway has a relatively high coverage rate in the eastern region."

Third, although this study focuses on the Chinese context, its findings still have some international applicability. For example, studies in countries like Morocco and Moldova show that regions with stronger green finance support, stricter environmental policies, and more developed DI are more likely to improve ER [85–88]. In practice, among developed countries, this study selected Germany as the example. It provides low-interest loans through policy banks like KfW to support innovation in photovoltaic and wind power and to strengthen PER through citizen energy cooperatives, thereby promoting green development in the energy sector. This approach is consistent with the green finance-enabled pathway (H1) in this study. Taking Brazil and Indonesia as examples among developing countries, Brazil has signaled a shift toward renewable energy through a nationwide unified electricity auction system, attracting large-scale commercial capital into the photovoltaic and wind power sectors, and achieving rapid energy structure replacement with limited fiscal subsidies. This aligns closely with pathway H2 in this study. Since 2020, Indonesia has launched a series of digital energy governance measures to achieve real-time monitoring and public disclosure of power company emissions and energy consumption. Simultaneously, Indonesia guides companies to apply and improve green technologies by mandating the shutdown of inefficient coal-fired power plants and enforcing emission quotas, consistent with the H3 pathway. These international practices demonstrate that green innovation ecosystems have universal significance in enhancing resilience and provide important references for all countries.

6. Conclusions and Implications

6.1. Conclusions

Enhancing ER is essential for regions facing external shocks and uncertainties and represents a necessary pathway for the sustainable development of energy systems. This study uses the dynamic QCA method across 30 provinces in China to explore how a green innovation ecosystem drives improvements in ER. With respect to the three core research questions outlined in the introduction, the following conclusions are drawn. First, a single factor in a green innovation ecosystem does not constitute a necessary condition for high ER. Instead, improving ER requires a synergistic combination of multiple factors. The results show that various factors can promote improvements in ER through three pathways: green finance-enabled, market-incentive-driven, and digital infrastructure-supported. Second, intra-group consistency analysis shows significant regional differences. The central region

has a high coverage of all three pathways, the western region has relatively weak overall adaptability, and the eastern region is dominated by the green finance-enabled pathway (H1). The varying applicability of configurations across different regions further reveals the diversity and complexity of pathways to improve ER. Third, overall consistency does not show a significant time effect. This indicates that the green innovation ecosystem's driving effect on ER is stable over time.

6.2. Theoretical Contributions

First, in terms of the theoretical framework, this study moves beyond single-perspective analyses of ER by proposing a "core layer–environmental layer–supporting layer" framework grounded in the green innovation ecosystem perspective. This study provides a novel analytical framework for ER research, offering insights into the underlying mechanisms that drive its enhancement.

Second, this study employs the dynamic QCA method. This method effectively incorporates the time dimension, dynamically identifying the characteristics of complex interactions among factors over time, thereby providing robust methodological support for ER research.

Finally, from a practical guidance perspective, the findings of this study provide evidence for differentiated policy design and for optimizing regional development strategies. The results show that different regions differ in their economic and financial foundations, industrial and energy structures, policy orientations, and transformation needs. Therefore, policy formulation needs to be combined with local contexts, with precise and adaptable support measures and innovative strategies implemented, which provide practical references for promoting ER enhancement across different regions.

6.3. Policy Implications

First, enhancing ER is a complex systemic theory and should be approached from a configurational perspective. Each region should, based on configurational thinking, focus on the interactions and coordination among the core, environmental, and supporting layers of green innovation from a holistic perspective. Furthermore, each region should, based on its own conditions and in line with high ER configuration templates, optimize the structure of its regional green innovation ecosystem through configurational optimization to achieve a structural combination of multiple elements and precise adaptation of development pathways.

Second, dual green innovation and PER have a certain universality in enhancing ER. Regions should increase sustained investment in both RGI and IGI, and fully mobilize public oversight and social participation.

Third, the eastern region, with its strong economic and financial foundation and high public environmental awareness, has the highest coverage of green finance-enabled pathways. On the one hand, it should improve the GF market, establish a green technology research and development risk compensation fund, and support the research and transformation of green innovation. On the other hand, it should strengthen environmental information disclosure and public participation mechanisms, promote the transformation of social demands into innovation, encourage targeted cooperation among universities, research institutions, and enterprises, and advance the green transformation of the energy industry.

Fourth, the central region has a solid industrial base and an urgent need for transformation, with relatively high coverage across all three pathways. On the one hand, it should improve local carbon markets and green electricity trading mechanisms to send a stable signal for energy transition. On the other hand, it should promote the integration

of environmental credit evaluation with financing facilitation and support enterprises to carry out green innovation based on the regional industrial base.

Fifth, the western region has a complex energy structure and an underdeveloped DI, resulting in relatively low coverage across all pathways. On the one hand, it can leverage national strategic plans such as the "Eastern Data and Western Computing" project to accelerate the construction of regional energy big data centers and intelligent dispatch platforms, thereby enabling cross-provincial collaboration among wind, solar, and hydropower. On the other hand, it can rely on digital platforms to support enterprises in optimizing energy systems and carrying out clean production transformation, enhancing the adaptability and recoverability of energy systems under resource constraints.

7. Research Limitations and Future Research Directions

While this study systematically revealed the multi-pathway effects of green innovation ecosystems driving ER enhancement, certain limitations remain. First, although QCA allows the use of linear or nonlinear calibration functions, researchers typically need to artificially set the critical points for "complete membership" and "complete non-membership," and the interpretation of results also relies on the researcher's subjective understanding. Second, the selection of antecedents focuses on explicit factors, potentially neglecting other potential internal and external factors. Third, due to the limited number of cases with low-level results and insufficient consistency, the study focuses only on the causal combination analysis of high-level results. Fourth, due to data availability limitations, this study temporarily uses panel data from 30 provinces over seven years as its research object. Future research can be deepened in the following directions: first, combine other quantitative methods to reduce the subjective influence in QCA studies. Second, identifying additional potential internal and external factors not included and analyzing their impact on ER and the specific mechanisms of action. Third, exploring the existence of robust ER configurational pathways over more extended periods, while clarifying typical configuration patterns for low-level ER.

Author Contributions: R.F.: writing—review and editing, methodology, and conceptualization. Y.L.: writing—original draft preparation, formal analysis, data curation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the MOE (Ministry of Education in China) Project of Humanities and Social Sciences, grant number 24YJA630124, Special Project of the Third Plenary Session of the Shanxi Provincial Philosophy and Social Sciences Planning, grant number 2024QH047YB, and Shanxi Provincial Philosophy and Social Sciences Planning Project, grant number 2024QN096.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: The Authors of this article would like to thank all the people who participated in this study. We thank the three reviewers for their detailed and constructive comments, and the editor for their guidance during the manuscript review process.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ER	Energy Resilience
RGI	Radical Green Innovation
IGI	Incremental Green Innovation
CER	Command-and-Control Environmental Regulation
MER	Market-Based Environmental Regulation
PER	Public Participation Environmental Regulation
GF	Green Finance
DI	Digital Infrastructure

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