Investigating Factors Influencing Regional Green Innovation Based on the Grouping Perspective

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Abstract. Amid global climate change, regional green innovation plays a pivotal role in sustainable development. This study employs Fuzzy-set Qualitative Comparative Analysis (fsQCA) to analyze 2022 Chinese provincial data, investigating how digital intelligence policies (digitalization and intelligence) drive green innovation. Key findings: (1) No single policy condition alone ensures high green innovation; (2) Digital attention is a core necessity for high innovation, while insufficient digital talent policy, government R&D funding, and IT infrastructure underpin low innovation; (3) High innovation requires synergies among digital attention, talent policies, and R&D budgets; (4) Non-high innovation stems from imbalances among these factors. The study offers configurational insights for optimizing green innovation strategies.

Keywords: Digital Intelligence Policy, Regional Green Innovation, Fuzzy-set Qualitative Comparative Analysis.

1. Introduction

Under China's national strategies of green development and ecological civilization construction, regional green innovation serves as a crucial mechanism to achieve carbon peaking/neutrality goals. This approach drives talent cultivation, accelerates green technology R&D, and enhances national innovation capacity in sustainable technologies, offering theoretical insights and practical references for advancing regional green innovation studies.

Prior research has explored diverse drivers of regional green innovation, including high-end manufacturing, innovation capacity, digital finance, and intelligent manufacturing. However, existing studies predominantly adopt singular-factor analyses, neglecting the synergistic mechanisms of digital-intelligent integration. This oversight limits understanding of how multi-dimensional policy configurations interactively shape RGI outcomes. Our study addresses this gap by systematically examining the coupling effects of digitalization and intelligence within a configurational framework.

This study adopts a configurational approach to examine how digital intelligence policies drive regional green innovation. Utilizing 2022 provincial-level data in China and fsQCA methodology, we analyze six critical influencing factors. Key contributions include: First, synthesizing prior research to identify six pivotal determinants of regional green innovation. Second, revealing distinct causal pathways through fsQCA and threshold-adjusted robustness tests. Third, demonstrating substitutability among condition combinations. Findings highlight that no single factor suffices, but synergistic configurations—particularly integrating digital prioritization, talent policies, and R&D funding—optimize outcomes. The study advances theoretical frameworks for innovation governance while offering evidence-based policy design principles.

2. Background

As for the influencing factors of regional green innovation, it can be divided into two dimensions: digital policy and intelligent policy.

2.1. The impact of digital policies on regional green innovation

Scholars have systematically examined four digital dimensions shaping regional green innovation: Digital talent policy, digital economic environment, digital development level, and digital prioritization. Xu & Wang (2024)[1] demonstrated through a two-stage Super-NSBM model that digital economy development significantly enhances green innovation efficiency. Yang et al. (2024)[2] applied time-varying DID models to urban panel data, confirming digital government transformation as a critical RGI catalyst. Huang et al. (2023)[3] identified via threshold models that digital talent agglomeration exerts a negative moderating effect on digital economy-RGI linkages, advocating adaptive talent policies. Han & Liu (2022)[4] established through mediation analysis that provincial digital economy development directly promotes green transition. These findings collectively highlight the multi-layered yet context-dependent nature of digital-RGI interactions, underscoring the necessity of policy coordination across dimensions.

2.2. The impact of smart policies on regional green innovation

Intelligent factors shaping regional green innovation primarily encompass government R&D funding and technological infrastructure. Chen et al. (2024)[5] employed spatial econometric and mediation models to demonstrate artificial intelligence's dual impact on green development: direct effects and indirect pathways through industrial restructuring and green technology advancement. García-Sánchez et al. (2020)[6] identified smart technologies as RGI accelerators via cross-border data analytics, enabling knowledge spillovers, real-time environmental governance, and clean-tech investments. These studies collectively emphasize intelligent systems' synergistic governance potential, where strategic resource allocation and digital infrastructure jointly catalyze green transitions through multi-scalar innovation mechanisms.

To sum up, the current research on the impact of digital intelligence on regional green innovation has achieved certain research results at the theoretical and practical levels, which has laid a solid foundation for in-depth research on the influencing factors of regional green innovation. However, most of the existing studies are limited to the analysis of a single conditional variable, and with the rapid development of society, regional green innovation has been affected by multiple complex factors, and it is an inevitable trend to explore the linkage mechanism of multiple factors.

3. Research method

3.1. Model Design

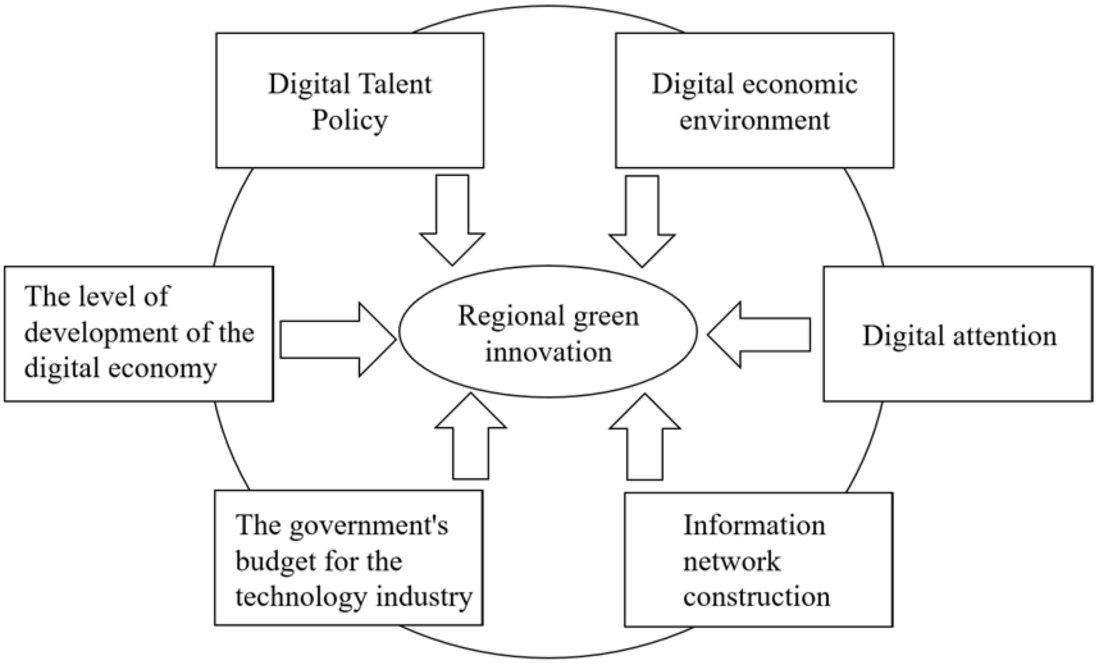

Figure1 Research ideas on influencing factors

The green innovation of a region is treated as the dependent variable, influenced by six identified explanatory variables. This study focuses on the mechanisms of digitization and intelligence within the context of coordinated development between the digital economy and green innovation, aiming to reveal how these factors drive regional green innovation through multiple pathways, including digital economic policies, optimization of the digital economic environment, government technology budget allocation, information network infrastructure construction, and enhanced digital attention. This approach shifts from traditional linear perspectives to a socio-technical complexity framework, emphasizing green innovation as an emergent outcome of interconnected systems. A graphical model is constructed to illustrate the research framework.

3.2. Methods

Although we have constructed a graph of the relationship between the conditional and outcome variables, the specific factors between them need to be studied. In order to analyze the specific influencing mechanism, based on the research of Shah [7] and other scholars, fsQCA was used for research. fsQCA is a research method that combines qualitative and quantitative analysis to explore how multiple conditional variables in small and medium-sized samples can lead to specific outcome variables in different combinations, especially for the analysis of complex causal relationships and nonlinear interactions. The specific reasons for this approach in this article are as follows.

First, capturing configurational effects of multiple concurrent conditions beyond single-variable determinism. Second, preserving contextual granularity through holistic case analysis while mitigating ecological fallacy inherent in large-sample averaging. Third, modeling asymmetric causal relationships where high-performance innovation pathways fundamentally differ from low-performance configurations—a critical divergence from linear regression's symmetry assumptions. Finally, fsQCA accommodates causal equifinality by identifying multiple distinct antecedent combinations that equivalently explain regional green innovation outcomes, thereby advancing complexity-theoretic understanding of digital-green transitions through systematic cross-case pattern recognition.

3.3. Variable indicators

3.3.1 Outcome variables

Regional Green Innovation Technologies (RGI). Drawing on the research of I. M, et al. (2024) [8], this paper uses the sum of green invention patents and utility model patents to add one to their natural logarithms.

3.3.2 Conditional variables

Based on the current literature and the availability of data, this paper divides the conditional variables into six factors, as shown in Table 1.

Table 1 Regional green innovation index system

First-level indicator	Secondary indicator	Short name	Three-level indicator	Data source	References
Regional green innovation	Regional green innovative technologies	RGI	The sum of green invention patents and utility model patents is taken as their natural logarithms after adding one	China Statistical Yearbook	I. M, et al. 2024[8]
Digitization	Digital Talent Policy	DTP	Proportion of computer services and software employees	China Statistical Yearbook	Huang X et al. 2023[9]
	Digital economic environment	DEP	Frequency of digital economy policy words	China Statistical Yearbook and National Bureau of Statistics	Shuai Hong et al. 2024[10]
	Digital Maturity	DED	Digital Economy Index	China Statistical Yearbook and National Bureau of Statistics	Lili Jiang et al. 2023[11]

Table 1 (continued)

First-level indicator	Secondary indicator	Short name	Three-level indicator	Data source	References
Intelligent	Digital attention	DA	Annual Search Index	China Statistical Yearbook	Hu et al. 2025[12]
	Government S&T Investment	GTB	Annual financial funding for scientific research	China Statistical Yearbook	H. Lian et al. 2024[13]
	Information network construction	INC	Number of 5G base stations	Economic Operation of the Communications Industry in 2022	H. Lian et al. 2024[13]

Table 1 delineates the digital-intelligence drivers of regional green innovation through six constitutive dimensions. The digitalization quadrant comprises: First, Digital talent policy - stimulating technological innovation ecosystems through strategic workforce development. Second, Digital economic environment - catalyzing industrial transition via green industry incubation platforms. Third, Digital maturity - enhancing innovation efficiency through smart resource allocation systems. Fourth, Digital attention - amplifying environmental governance via technology-mediated public participation. The intelligence dimension features: First, Government S&T investment - fostering industry-academia symbiosis through innovation cluster development. Second Information network construction - accelerating green technology diffusion through intelligent connectivity frameworks. These constructs collectively operationalize the socio-technical mechanisms underlying sustainable regional transformation.

3.4. Data sources and calibration

3.4.1 Data source

The research data in this paper are from 31 provinces and cities in China (excluding Hong Kong, Macao and Taiwan) in 2022, and the data are from the China Statistical Yearbook, the National Bureau of Statistics, and the Economic Operation of the Communications Industry in 2022. In order to ensure the integrity and reliability of the data, the data that are missing in some regions are replaced by the data available in the last year.

3.4.2 Data calibration

Data calibration needs to determine the set membership score, which is determined as "fully affiliated", "intersectional", and "completely unaffiliated" 3 "anchor points". In this paper, based on the research of Hasan, N and Bao, YK (2022) [14], the three "anchor points" are calibrated according to the 95%, 50% and 5% quantiles, respectively, and the calibration results are shown in Table 2:

Table 2 Variable calibration

Conditions and outcome variables	Full affiliation	Intersections	Not affiliated at all
Table 2 (continued)			
DA	235	132	0
DEP	12318.2	7953	5353
DTP	60.728	8.3	0.96
DED	0.6594	0.271	0.2292
GTB	4066	620.9	20.08
INC	23.6	7.9	0.98
RGI	10.59	8.61	5.84

Table 2 presents critical calibration thresholds for fsQCA variables, with membership parameters quantified as follows: $DA(FM = 235, IS = 132, CN = 0), DEP(FM = 12318.2, IS = 7953, CN = 5353), GTB\ (FM = 4066, IS = 620.9, CN = 20.08), INC\ (FM = 23.6, IS = 7.9, CN = 0.98), RGI\ (FM = 10.59, IS = 8.61, CN = 5.84)$. These fuzzy-set anchors establish empirical boundaries for multi-conjunctural causality testing, operationalizing continuous variables into qualitatively meaningful membership states essential for identifying sufficient condition sets and configuring causal pathways. The calibrated thresholds ensure analytical rigor in determining asymmetric relationships between antecedent configurations and outcome attainment.

4. Empirical analysis and discussion

4.1. Necessity analysis

According to Chen, Wen (2021) [15], and others, the necessity analysis of fsQCA examines whether individual circumstances may be necessary for an outcome to occur. When the consistency level is higher than 0.9, the conditional variable is a necessary condition. Table 3 shows the results of the necessary condition analysis:

Table 3 Necessity analysis

Sets of conditions	RGI		~RGI	
	Consistency	Coverage	Consistency	Coverage
DA	0.944	0.886	0.618	0.601
~DA	0.576	0.592	0.883	0.942
DEP	0.758	0.730	0.691	0.691
~DEP	0.680	0.680	0.731	0.758
DTP	0.856	0.965	0.446	0.521
~DTP	0.576	0.501	0.970	0.875
DED	0.813	0.898	0.479	0.549
~DED	0.591	0.523	0.911	0.834
GTB	0.844	0.983	0.420	0.507
~GTB	0.577	0.490	0.986	0.868
INC	0.847	0.905	0.529	0.586
~INC	0.613	0.557	0.914	0.861

Note: ~ indicates logical not.

As can be seen from Table 3, DA is a necessary condition for RGI, and ~DTP, ~GTB, and ~INC are necessary conditions for ~RGI.

4.2. High-level RGI configuration analysis

Configuration analysis is an analytical method used to study the influence of multiple factors on the results, which emphasizes the interdependence, interweaving and interaction of elements from the perspective of system integrity, and can reveal how multiple factors affect the results together. In this method, after calibrating each variable, the fsQCA analysis tool was used to construct a truth table, and the frequency threshold was set to 1 and the consistency threshold was set to 0.89 according to Zhang (2025) [16] et al. The configuration of this paper is mainly based on the nested relationship between the intermediate solution and the simple solution, where ● represents the existence of core conditions, ● the existence of auxiliary conditions, the ⊗absence of core conditions, the absence of ⊗ auxiliary conditions, and the absence of blank conditions. The results are collated as shown in Table 4:

Table 4 Configuration analysis of high and low RGI

Configuration	RGI		~RGI	
	1	2	3	4
DA	●	●	⊗	⊗
DEP		●		⊗
DTP	●	●	⊗	⊗
DED		●	⊗	
GTB	●	●	⊗	⊗
INC	●		⊗	⊗
Consistency	0.998	1	0.970	0.971
Raw Coverage	0.727	0.576	0.778	0.669
Unique Coverage	0.181	0.030	0.140	0.032
Overall solution Consistency	0.998		0.971	
Overall solution Coverage	0.757		0.809	

The configuration paths 1 and 2 driven by DA, DTP, AND GTB indicate the existence of DA, DTP, and GTB as the core conditions, which can lead to high-level regional green innovation.

Digital attention-digital talent policy-government science and technology industry budget-information network construction-driven path. Corresponding to configuration 1 in the table, INC exists as an auxiliary condition, and DEP and DED can exist or not, representing Guangdong, Jiangsu, Zhejiang, Shandong, Henan, Hubei, Beijing, Hebei and Anhui. For example, the scale of the digital economy in Jiangsu Province in 2022 will be 5.5 trillion yuan, and the Internet of Things and big data technologies will be deeply applied to environmental monitoring and other fields. 30% of the fiscal science and technology expenditure is invested in the research and development of green technologies such as new energy, and enterprises are promoted to tackle key problems through the mechanism of "unveiling the leader"; Policies such as the "Entrepreneurship and Entrepreneurship Plan" gather top talents from around the world; The number of 5G base stations ranks second in the country, supporting digital and green innovation.

Digital attention-digital talent policy-government budget for science and technology industry-digital economic environment-digital economy development level-driven path. Configuration 2 in the corresponding table, DEP and DED exist as auxiliary conditions, and INC can exist or not, representing Guangdong, Shandong, Sichuan, Shanghai, Fujian, Shaanxi, and Anhui. For example, Shanghai has built the world's largest 5G+AI city perception network, deploying more than 60 IoT terminals to collect environmental data in real time. set up a 5 billion yuan hydrogen energy fund; The "Pujiang Talent Plan" has a maximum funding of 20 million yuan, and colleges and universities set up "digital carbon neutrality" disciplines, and foreign talents have "one certificate for all"; The proportion of the digital economy is accelerating the development of green innovation.

4.3. Non-high-level RGI configuration analysis

For configuration pathway 3, DA, DTP, GTB, and INC are missing as the core conditions, resulting in non-high-level regional green innovation, and DED is missing as an auxiliary condition. The representative provinces are Ningxia, Hainan, Qinghai, Xinjiang, Gansu, Inner Mongolia, Jilin, Heilongjiang, Shaanxi and Jiangxi. For example, from the collected data, it can be seen that Xinjiang's attention to digitalization, the government's budget for the technology industry, the digital talent policy, and the construction of information networks rank relatively low in the country, and the degree of digital development is low, which is why the level of green innovation is not high.

For configuration path 4, DA, DTP, GTB, and INC are missing as the core conditions, resulting in non-high-level regional green innovation, and DEP is missing as auxiliary conditions. The representative provinces are Xizang, Ningxia, Hainan, Inner Mongolia, Jiangxi and Gansu. For example, Xizang is vast and sparsely populated, with high-altitude areas accounting for 86% of the region's area, and the construction cost of optical fiber and base stations is 5-8 times that of plain areas, and the number of 5G base stations is scarce. Xizang 's R&D funding for green technology mainly relies on transfer payments from the central government, and local supporting capacity is weak. Despite the implementation of the " Xizang Special Allowance", the number of talents introduced is still very scarce; At the same time, the network latency in agricultural and pastoral areas generally exceeds 200 ms, which is difficult to support green technology innovation scenarios such as real-time environmental monitoring and remote energy dispatching.

4.4. Robustness test

In this paper, the consistency threshold of conditional configuration adequacy is changed from 0.8 to 0.85, and the frequency threshold is changed from 1 to 2, and the results are shown in Table 5. If the result path is almost the same as the result path in Table 4, the result is robust. The results in Table 5 show that both the overall consistency and individual consistency are greater than 0.9, and the consistency level and configuration path are almost consistent with those in Table 4, indicating that the results are robust.

Table 5 Robustness test

Configuration	Threshold changed to 0.85		For consistency read 2	
	1	2	3	4
DA	●	●	●	●
DEP		●	●	
DTP	●	●	●	●
DED		●	●	●
GTB	●	●	●	●
INC	●			●
Consistency	0.998	1	1	0.998
Raw Coverage	0.727	0.576	0.576	0.662
Unique Coverage	0.181	0.030	0.030	0.116
Overall solution Consistency	0.998		0.998	
Overall solution Coverage	0.757		0.692	

Table 5 (continued)

5. Conclusions and implications

5.1. Conclusions of the study

This study employs fsQCA on 2022 provincial data to elucidate the conjunctural causation mechanisms underlying China's regional green innovation systems. Key findings reveal: The influence of a single conditional variable on high-level regional green innovation is limited, indicating that a single factor is insufficient to constrain the improvement of regional green innovation levels. However, the focus on digitization constitutes a necessary condition for high-level regional green innovation, while regions with lower levels rely on the combined effects of conditions such as digital talent policies, government science and technology budgets, and information network construction. Further analysis indicates that the focus on digitization, digital talent policies, and government science and technology industry budgets are the core conditions for high-level regional green innovation. Specifically, Configuration 1 consists of the interactive matching of digitization focus, digital talent policies, government science and technology industry budgets, and information network construction, representing regions such as Guangdong and Jiangsu. Configuration 2 is constituted by the interactive matching of digitization focus, digital talent policies, government science and technology industry budgets, digital economy environment, and digital economy development level, representing regions such as Guangdong and Shandong. In the context of green innovation in non-high-level areas, the focus on digitization, digital talent policies, government science and technology industry budgets, and information network construction are key influencing factors. This result further verifies the asymmetry between the configuration paths.

5.2. Deficiencies and prospects

In this paper, fsQCA is used to study the influencing factors of regional green innovation, but there are still the following shortcomings:

First, fsQCA only uses single-year data, which can be extended to multi-year dynamic analysis in the future. Second, the influencing factors of regional green innovation only cover six dimensions, and more factors can be included in the follow-up in-depth research. Third, the current analysis level focuses on provincial-level administrative regions. In the future, it can be refined to the county or enterprise level to carry out more granular discussions..

Reference

[1] Xu H, Wang J. Digital economy, regional cooperative innovation and green innovation efficiency: Game model and empirical evidence based on regions in China[J]. Sustainability, 2024, 16(12): 5161.

[2] Yang X, Ran R, Chen Y, et al. Does digital government transformation drive regional green innovation? Evidence from cities in China[J]. Energy Policy, 2024, 187: 114017.

[3] Huang X, Zhang S, Zhang J, et al. Research on the impact of digital economy on regional green technology innovation: Moderating effect of digital talent aggregation[J]. Environmental Science and Pollution Research, 2023, 30(29): 74409-74425.

[4] Han D, Liu M. How does the digital economy contribute to regional green development in China? Evidence-based on the intermediary effect of technological innovation[J]. Sustainability, 2022, 14(18): 11147.

[5] Chen M, Wang S, Wang X. How does artificial intelligence impact green development? Evidence from China[J]. Sustainability, 2024, 16(3): 1260.

[6] García-Sánchez, I. M., Rodríguez-Domínguez, L., & Gallego-Álvarez, I. Smart technologies and green innovation in regional development: A cross-country analysis. Journal of Cleaner Production, 2020, 267: 122456.

[7] Shah S K, Tang Z, Yuan J, et al. Complexity in the use of 5G technology in China: An exploration using fsQCA approach[J]. Journal of Intelligent & Fuzzy Systems, 2023, 45(2): 2193-2207.

[8] Liu M, Liu L, Feng A. The impact of green innovation on corporate performance: An analysis based on substantive and strategic green innovations[J]. Sustainability, 2024, 16(6): 2588.

[9] Huang, X, Zhang, S, Zhang, J. & Yang, K. Research on the impact of digital economy on regional green technology innovation: Moderating effect of digital talent aggregation. Environ. Sci. Pollut. Res. 2023, 30: 74409–74425.

[10] Hong S, Wang T, Fu X, et al. Research on quantitative evaluation of digital economy policy in China based on the PMC index model[J]. PLOS One, 2024, 19(2): e0298312.

[11] Li T, Yang L. The effects of tax reduction and fee reduction policies on the digital economy[J]. Sustainability, 2021, 13(14): 7611.

[12] Hu R, Song K. Carbon reduction effects of government digital attention[J]. Frontiers in Environmental Science, 2025, 13: 1539223.

[13] Lian H, Min B, Oh J. State-led smart city policy changes and impacts on urban growth and management: A study of 118 Chinese smart cities[J]. Journal of Asian Architecture and Building Engineering, 2024, 12: 1.

[14] Hasan N, Bao Y. A mixed-method approach to assess users’ intention to use mobile health (mHealth) using PLS-SEM and fsQCA[J]. Aslib Journal of Information Management, 2022, 74(4): 589-630.

[15] Chen W, Song X J, Li Y. Factors affecting the sustainable development of HRS in transforming economies: A fsQCA approach[J]. Sustainability, 2021, 13(4): 1727.

[16] Zhang J, Yang Z, Zhang X, et al. Institutional configuration study of urban green economic efficiency - analysis based on fsQCA and NCA[J]. Polish Journal Of Environmental Studies, 2025, 34(2): 1457.