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Digital Transformation and Green Innovation Performance in New Energy Enterprises: A Configurational Analysis of Complex Resource Systems Using fsQCA

Xiangyu Chen [1,2], Xiaofeng Xu [3,4] and Da Tong [5,6,*]

[1] KoGuan School of Law, Shanghai Jiao Tong University, Shanghai 200030, China; 2321050029@ecupl.edu.cn
[2] Law School, East China University of Political Science and Law, Shanghai 200042, China
[3] International School of Law and Finance, East China University of Political Science and Law, Shanghai 200042, China; 2898@ecupl.edu.cn
[4] Institute for Energy Economics and Policy, China University of Petroleum East China, Qingdao 266580, China
[5] Institute of Circular Economy, Tongji University, Shanghai 200092, China
[6] School of International Relations & Public Affairs, Fudan University, Shanghai 200433, China
* Correspondence: 24260170099@m.fudan.edu.cn

Abstract

Green innovation performance (GIP) in new energy enterprises emerges from complex interactions among technological, organizational, and institutional resource subsystems, yet existing research predominantly applies linear, single-factor approaches that fail to capture this systemic complexity. Drawing on the Resource-Based View (RBV) and systems thinking, this study employs fuzzy-set qualitative comparative analysis (fsQCA) on a sample of 54 Chinese A-share listed new energy enterprises—spanning wind power, solar power, hydrogen energy, energy storage, and new energy equipment manufacturing—observed over the 2019–2023 period, to examine the configurational pathways through which these firms achieve high GIP. Green patent grants serve as the outcome measure, and six conditions spanning three resource subsystems are considered: digital transformation and R&D intensity (technological subsystem), firm size and ownership structure (organizational subsystem), and government subsidies and carbon emission performance (institutional subsystem). Three key findings emerge. First, none of the six conditions is individually necessary for high GIP (all consistency scores below 0.90), indicating that high GIP reflects combinations of resources rather than a single driver. Second, the six sufficient configurations identified collapse into two distinct pathway clusters: a "SOE digital-empowerment-driven" cluster, in which digital transformation combines with R&D investment, government subsidies, or organizational scale within state-owned enterprises, and a "resource–capability synergy and substitution" cluster, in which scale resources, R&D investment, and policy support combine with or substitute for digital transformation regardless of ownership. Third, digital transformation appears in five of the six pathways, indicating that it functions as a key—but not universal—enabling element whose effectiveness depends on its alignment with other system components. Beyond confirming that multiple, equally valid resource combinations lead to high GIP, this study's principal contribution is to embed RBV within an explicit systems framework, showing how technological, organizational, and institutional resources interact as subsystems of a single socio-technical system, and to translate the resulting configurations into differentiated, pathway-specific guidance for enterprises and policymakers navigating the low-carbon energy transition.

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1. Introduction

In this study, new energy enterprises refer to firms engaged in the generation, storage, or equipment manufacturing of non-fossil energy—chiefly wind power, solar power, hydrogen energy, and energy storage—which together constitute the industrial core of China's low-carbon energy transition. For readers less familiar with China's institutional context: firms in this sector range from large, centrally or locally state-owned enterprises (SOEs)—typically former state monopolies or state-backed champions in wind, solar, or grid-related equipment—to privately founded, market-listed manufacturers and technology firms; SOEs are distinguished by state ownership of a controlling equity stake and are typically subject to closer government oversight, industrial-policy mandates, and performance evaluation on non-financial criteria (e.g., emissions targets) in addition to profitability, whereas private firms answer primarily to private shareholders and market competition. Both ownership types operate in the same regulated markets and compete for the same government subsidies, but, as detailed in Section 3.2, they differ systematically in scale, access to policy resources, and reporting obligations, which is why ownership structure (SOE) is analyzed here as a conditional variable rather than a fixed sample characteristic. Against the backdrop of accelerating progress toward the "dual carbon" goals (China's national pledge to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060) and the green transition of the energy structure, these enterprises play an important role in low-carbon energy transformation, and their green innovation performance (GIP)—that is, the output and effectiveness of a firm's green product, process, and management innovation activities—is central to clean-energy upgrading [1,2]. The full implementation of the Paris Agreement and the continuous advancement of China's "carbon peak and carbon neutrality" strategic goals mean that new energy enterprises not only face increasingly stringent carbon constraints and green performance requirements but also need to achieve systemic breakthroughs across multiple dimensions, including green technology R&D, improved clean energy utilization efficiency, and low-carbon business model innovation [2,3]. However, the GIP of new energy enterprises exhibits significant complexity and heterogeneity. Due to differences in technological foundations, organizational capabilities, and institutional environments, GIP outcomes are highly differentiated [2,4]. In practice, firms still face challenges such as insufficient technological accumulation, capital investment pressure, and unclear implementation pathways [3,4]. This raises the question of how firms can improve GIP under multiple constraints.

Against this backdrop, digital transformation has gradually emerged as a vital endogenous driver of green innovation in new energy enterprises [5,6]. The RBV posits that a firm's competitive advantage stems from heterogeneous resources and capabilities satisfying value, rarity, inimitability, and non-substitutability (VRIN) criteria [7]. In the context of this study, RBV is used to frame GIP as the outcome of how new energy enterprises combine heterogeneous technological, organizational, and institutional resources—rather than of any single resource in isolation—so that digital transformation is treated as one strategic resource among several that must be jointly configured to generate green innovation outcomes. Digital transformation—by reshaping data assets, algorithmic capabilities, and intelligent operational systems—constitutes a systematic restructuring of internal strategic resources. By deepening digital transformation, new energy enterprises can strengthen precise control over energy, information, and value flows while organically integrating

digital technologies with R&D investment and organizational capabilities, forming a heterogeneous resource portfolio that supports green innovation [5,6]. However, existing research remains largely fragmented along two separate strands: one strand focuses on the isolated impact of digitalization on corporate performance [5,6,8,9], while a second, largely separate strand examines R&D investment, firm characteristics, and the institutional environment as independent predictors of green innovation [10–13]. Few studies bridge these two strands to examine how digital transformation, together with R&D investment, corporate characteristics, and the institutional environment, collectively constitute a resource allocation pathway driving GIP.

Furthermore, GIP in new energy enterprises can be understood as an emergent outcome of a complex resource system in which technological, organizational, and institutional subsystems interact in non-linear and context-dependent ways. RBV theory emphasizes the complementarity and synergy of resources; performance improvements often depend on the coordinated allocation of multiple resources rather than the linear effect of a single factor [10]. Yet existing literature on corporate green innovation predominantly employs regression analysis, focusing on the marginal effects of individual variables and neglecting the interactive configurational effects among resources [11]. In reality, GIP results from the synergistic interaction of multiple conditions, including digital transformation level, R&D investment, firm size, ownership structure, government subsidies, and carbon emission performance [10,12,13]. Due to differences in resource endowments, firms may achieve similarly high GIP through diverse resource combination pathways, exhibiting "multiple conjunctural causation" and "equifinality" (a given condition's effect on the outcome depends on which other conditions are present alongside it, rather than acting the same way in every firm, and different combinations of conditions can lead to the same outcome, so there is no single route to high GIP) [11]. Relying solely on linear analytical frameworks makes it difficult to uncover the complex resource allocation mechanisms underlying green innovation. These configurational patterns have been documented primarily in general manufacturing and traditional-energy contexts [10,12,13], whereas empirical evidence on how such resource configurations operate specifically within new energy enterprises remains scarce, which motivates the empirical focus of this study. Chinese new energy enterprises possess distinct institutional characteristics in terms of policy orientation, government support, and ownership structure; the mechanisms through which these institutional resources shape resource acquisition and allocation behavior remain insufficiently explored [12,13].

Based on this context and theoretical foundation, this paper adopts RBV as its core theoretical perspective and digital transformation as its primary entry point to systematically explore the multi-path resource allocation mechanisms through which new energy enterprises achieve high GIP. Using Chinese A-share listed new energy enterprises as the sample and employing fsQCA, this study identifies how different resource condition combinations jointly drive high GIP and reveals the differences and underlying logic among multiple equivalent pathways. This paper addresses two research questions: (RQ1) What configurations of technological, organizational, and institutional resources are sufficient for new energy enterprises to achieve high GIP, and is any single condition necessary on its own? (RQ2) How does digital transformation function as an enabling condition across these configurations, and how do the resulting equivalent pathways reflect distinct resource endowment structures among new energy enterprises?

We note that this paper does not formulate directional hypotheses in the conventional net-effects sense (e.g., "H1: DIG positively affects GIP"). This follows standard practice in configurational fsQCA research: because the method examines how conditions combine into configurations rather than estimating the independent, average effect of each condition,

we instead state two configurational propositions guiding the analysis. Proposition 1: no single technological, organizational, or institutional condition among the six examined is expected to be individually necessary for high GIP. Proposition 2: multiple, distinct combinations of these conditions are expected to be sufficient for high GIP, with digital transformation playing an enabling role in some, but not necessarily all, of these combinations. These propositions are examined empirically via the necessary-condition analysis (Section 3.4) and the sufficient-condition configurational analysis (Section 4), respectively.

The contributions of this study are threefold. First, it moves beyond single-variable and linear explanations by introducing RBV into the configurational analysis of GIP in new energy enterprises. From the perspective of resource synergy, it reveals the complex mechanisms through which digital transformation, together with other technological, organizational, and institutional conditions, jointly drive high GIP, thereby extending RBV applications in green innovation research. Second, by employing fsQCA, the study systematically identifies multiple equifinal configurational pathways to high GIP, revealing that new energy enterprises can attain superior green innovation performance through distinct, equally valid combinations of resources rather than a single universal formula, and clarifying the specific conditions under which digital transformation functions as an effective enabling resource. Third, by distinguishing a "SOE digital-empowerment-driven" pathway cluster from a "resource–capability synergy and substitution" cluster, the study translates these configurations into differentiated, ownership- and resource-specific policy and managerial guidance, moving beyond the generic prescription to "invest in digital transformation" toward recommendations tailored to a firm's specific resource endowment.

2. Literature Review

2.1. Digital Transformation

Digital transformation has become an important route through which firms build competitive advantage and pursue sustainable development [14,15]. Digital transformation refers to the process by which enterprises systematically introduce and deeply apply next-generation digital technologies—such as big data, cloud computing, artificial intelligence, and the Industrial Internet—to fundamentally restructure their business models, organizational structures, operational processes, and value creation methods [14,16]. Unlike traditional IT upgrades, digital transformation emphasizes the deep integration of technology and organizational capabilities, representing a systemic transformation that encompasses strategy, culture, and processes [15,16].

The impact of digital transformation on corporate performance and innovation behavior has received widespread attention [8,9]. From an internal perspective, digital transformation significantly improves resource allocation efficiency and operational management capabilities by enhancing data processing capacity and intelligent decision-making [8]. Firms with higher digitalization levels typically possess stronger knowledge integration and organizational learning capabilities, facilitating sustained technological innovation [9]. From the perspective of external effects, digital transformation further strengthens firms' adaptability and value creation potential by reducing information asymmetry, enhancing supply chain coordination, and expanding market boundaries [17].

In the context of green development, the effects of digital transformation on corporate environmental performance and green innovation are attracting increasing academic attention. Research finds that digital technology applications can effectively reduce corporate energy consumption and carbon emission intensity while enhancing green production efficiency. Digital tools support corporate green transformation through real-time energy monitoring, process optimization, and clean technology diffusion. Particularly in the new energy sector, digital integration enables intelligent management across the clean en-

ergy lifecycle—from development and production to storage and utilization—thereby facilitating technological iteration and supporting energy conservation and emission reduction targets [17,18].

However, existing research on digital transformation still faces limitations. Most studies rely on linear regression to reveal the net effect of digital transformation on a single outcome variable, neglecting its interactive relationships with other internal and external conditions [19,20]. How digital transformation synergizes with R&D investment, firm characteristics, and the institutional environment to form resource allocation pathways that drive GIP remains a critical issue requiring further exploration [19,20].

2.2. Green Innovation Performance

Green innovation refers to innovative activities in which enterprises integrate environmental protection concepts into product R&D, process improvement, organizational management, and business model innovation, aiming to reduce resource consumption, minimize pollution emissions, and enhance ecological benefits [21,22]. Compared to general technological innovation, green innovation possesses dual economic and environmental attributes; its realization depends not only on internal technological accumulation and R&D capabilities but is also significantly influenced by external institutional pressures and market demand [22,23]. GIP represents a comprehensive evaluation of the output levels and outcomes of a company's green innovation activities, typically encompassing green product, process, and management innovation [21,24].

Existing research primarily explores the mechanisms influencing corporate GIP from three levels: technological, organizational, and institutional. At the technological level, R&D intensity (RDI) is widely regarded as a core driver; sufficient R&D resources not only strengthen a firm's technology absorption capacity but also accelerate clean technology development and application [23,25]. At the organizational level, firm size and ownership structure significantly moderate GIP outcomes. Larger firms typically possess stronger financial foundations and innovation management systems, facilitating the large-scale application of green technologies; meanwhile, SOEs bearing greater policy compliance responsibilities often exhibit behavioral characteristics in green innovation that differ from those of private enterprises [26,27]. At the institutional level, government subsidies and environmental regulations serve as key external drivers. Government subsidies incentivize green technology R&D investment by reducing R&D risks and costs; carbon constraints drive firms to intensify green innovation through a "backward-pressure mechanism" [28–31].

In the field of green innovation among new energy enterprises, research reveals the following characteristics. First, although new energy enterprises focus primarily on clean energy development, they still face practical pressures regarding carbon performance, process greening, and low-carbon supply chain management [28,29]. Second, green innovation in new energy enterprises relies heavily on technological breakthroughs and capital-intensive investment [23,25]. Third, digital technologies are gradually emerging as a new driving force for green innovation in these enterprises, yet the synergistic mechanisms between the two remain insufficiently elucidated [24,25]. Across this body of work, there is broad agreement that digital transformation, R&D intensity, firm size, ownership, subsidies, and carbon performance are each relevant to GIP, but comparatively little agreement on their relative importance, since net-effect estimates for the same condition can differ across samples, industries, and model specifications. This is consistent with our starting premise: if a condition's relationship with GIP depends on which other conditions co-occur with it, a framework that estimates one average effect per condition across the whole sample is not well positioned to adjudicate between these differing estimates. Accordingly, this study's

contribution is not to add digital transformation as one further variable alongside those already studied, but to reframe the six conditions as three interacting resource subsystems (Section 2.3) whose joint configurations, rather than individual net effects, are examined as the determinants of high GIP.

Overall, existing GIP research remains focused on net-effect analysis (regression-style analysis that estimates each variable's average, independent contribution to the outcome while holding the others constant), leaving open exactly the kind of multidimensional condition combinations and equivalent pathways that this study investigates.

2.3. Resource-Based View

The RBV, proposed by Wernerfelt and systematically developed by Barney, has become one of the most influential theories in strategic management [7,32]. Its core tenet holds that a firm's sustainable competitive advantage lies in heterogeneous resources and unique capabilities satisfying the VRIN criteria [7,33]. RBV conceives of a firm as a collection of heterogeneous resources, emphasizing that differences in internal resource endowments are the fundamental cause of performance differentiation [32,33].

In the evolution of this theory, scholars have introduced the perspective of dynamic capabilities, emphasizing that a firm's ability to integrate, reconfigure, and renew its resource portfolio in a dynamic environment is equally critical to maintaining competitive advantage [34–36]. This perspective offers significant insights for understanding GIP formation in new energy enterprises: digital transformation is not merely technology adoption but a systematic reshaping of a firm's resource structure and capability system, building new digital assets and intelligent operational capabilities to form a strategic resource portfolio supporting green innovation [36,37].

In the field of green innovation, RBV provides a crucial theoretical foundation for understanding differentiated GIP. Existing research indicates that technological, organizational, and institutional resources collectively constitute the multidimensional resource conditions influencing GIP [37–39]. These resources do not operate in isolation but generate synergies through complementary integration, jointly driving enhanced green innovation capability [38,39]. Particularly in the new energy sector, the introduction of digital resources has significantly altered the composition of firms' technological resources, making the synergistic configuration of digital transformation with R&D investment, firm characteristics, and institutional resources a key factor in understanding GIP differentiation [37–39].

Building on the RBV framework, this study organizes the six conditional variables into three resource subsystems that jointly constitute the socio-technical system through which new energy enterprises pursue green innovation. The first is the technological resource subsystem, comprising digital transformation level (DIG) and R&D intensity (RDI), which captures a firm's capacity to generate, absorb, and deploy innovation-enabling knowledge and capabilities. The second is the organizational resource subsystem, comprising firm size (SIZE) and ownership structure (SOE), which reflect the structural and institutional endowments that determine a firm's ability to mobilize and coordinate resources for green innovation. The third is the institutional resource subsystem, comprising government subsidies (SUB) and carbon emission performance (CARB), which represent the external policy environment and regulatory pressures that shape firms' green innovation incentives and constraints. These three subsystems do not operate independently; rather, they interact in complex, non-linear ways to produce GIP as a system-level outcome. This tripartite resource framework bridges RBV theory with a systems perspective, providing the analytical foundation for the configurational analysis that follows.

Importantly, RBV emphasizes the combined effects of resources and their context dependence; synergistic allocation of different resource conditions may yield divergent

outcomes across different corporate contexts [35,36]. This characteristic aligns closely with the core logic of configurational analysis: different firms may achieve similarly high GIP through distinct resource combination pathways, exhibiting the characteristics of "multiple conjunctural causation" and "equifinality" [40]. However, existing green innovation research based on RBV predominantly employs linear methods, making it difficult to uncover the complex mechanisms of multi-resource synergy or to identify multiple parallel equivalent pathways across different corporate contexts [38–40].

Taken together, the three literature domains reviewed above map directly onto the tripartite resource-subsystem framework that structures this study and connect back to RBV as follows. The digital transformation and green innovation performance studies (Sections 2.1 and 2.2) jointly inform the technological resource subsystem (DIG, RDI), which corresponds to the "valuable and rare technological capability" leg of VRIN; the organizational-level findings on firm size and ownership reviewed in Section 2.2 inform the organizational resource subsystem (SIZE, SOE), corresponding to the firm's capacity to mobilize and combine resources; and the institutional-level findings on subsidies and carbon regulation reviewed in Section 2.2 inform the institutional resource subsystem (SUB, CARB), corresponding to the external conditions that make internal resources valuable or exploitable in a given policy context. RBV, and, in particular, its emphasis on resource complementarity and context dependence (Section 2.3), supplies the theoretical rationale for treating these three subsystems as jointly, rather than independently, determining GIP, and it is this joint, non-linear determination that motivates the configurational (fsQCA) approach adopted in Section 3. This integrative logic—literature domain → resource subsystem → RBV construct → configurational role—is illustrated schematically in Figure 1 and underpins the variable selection described in Section 3.2.

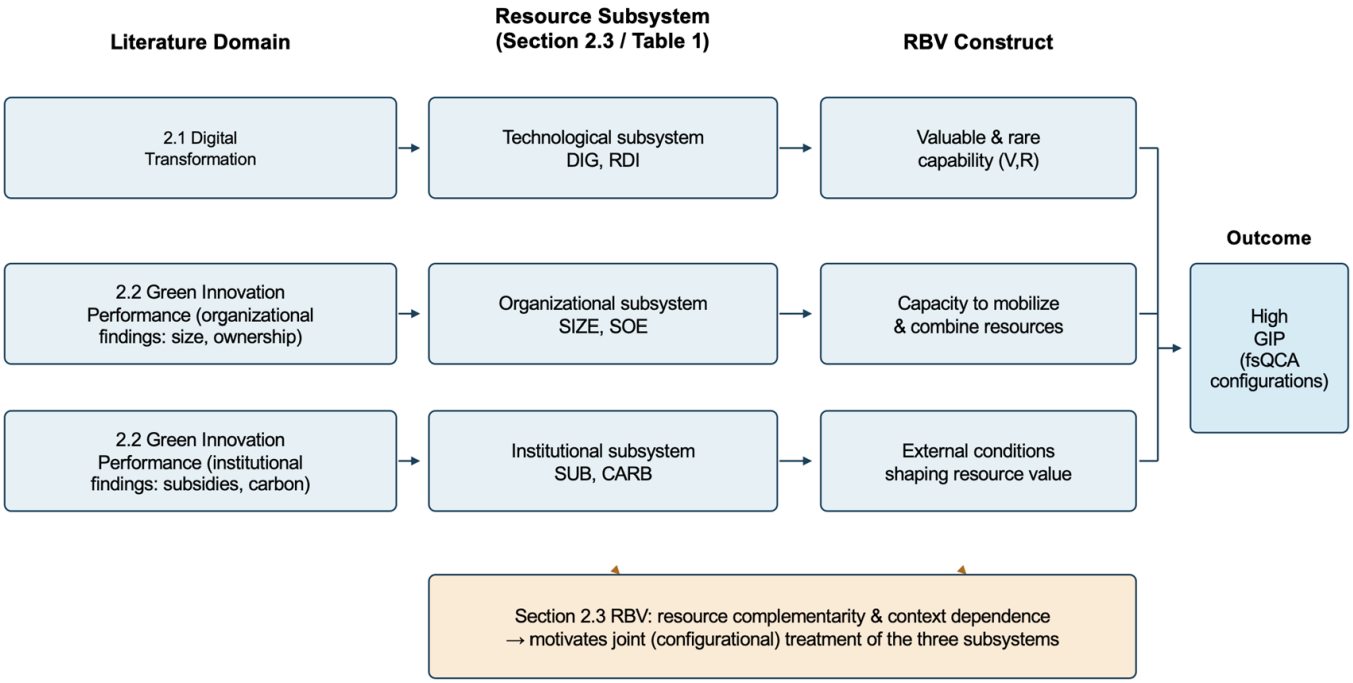


Figure 1. Integrative framework linking literature domains, resource subsystems, and RBV constructs to the fsQCA outcome.

3. Model Specification

3.1. Research Method and Data Sources

Traditional econometric methods are well-suited to identifying the net effect of individual variables, but are less capable of capturing the configurational causality inherent

in complex systems. Since GIP depends on the combined effects of multiple resources and capabilities interacting as a system, this study adopts fsQCA to examine how digital transformation, RDI, firm size, ownership structure, government subsidies, and carbon emission performance jointly form multiple pathways to high GIP [41–45]. In line with fsQCA best-practice guidance, the workflow also makes explicit the calibration logic, truth-table construction, necessity and sufficiency interpretation, and threshold-based robustness checks [43–45]. fsQCA, grounded in set theory and Boolean algebra, identifies sufficient and necessary conditions for outcomes, capturing the non-linear and context-dependent interactions among conditions that characterize complex causal systems. Concretely, the analysis proceeds in four steps, each reported in the corresponding subsection below: (i) calibration of the outcome and the six conditions into fuzzy-set membership scores (Section 3.3); (ii) necessary condition analysis, in which each condition's consistency for high GIP is checked against the 0.90 threshold (Section 3.4); (iii) construction of the truth table and its reduction via the Quine–McCluskey algorithm to derive complex, intermediate, and parsimonious solutions, from which core and peripheral conditions are distinguished (Section 4); and (iv) a robustness check that raises the consistency threshold and re-runs the truth table analysis to verify that the configurational structure is not an artifact of threshold choice (Section 4.3).

In plain terms, fsQCA treats each firm as a specific combination (a "configuration") of the six conditions, rather than estimating one average effect for each condition in isolation as regression does. Each condition and the outcome are first rescaled ("calibrated") onto a 0-to-1 membership scale, where 0 means a firm is fully outside a given set (e.g., fully outside the "high digital transformation" group) and 1 means it is fully inside; values near 0.5 are the most ambiguous cases. For every combination of conditions observed in the data, the analysis then computes two numbers: consistency, which asks how reliably that combination coincides with high GIP (analogous to a hit rate), and coverage, which asks what share of high-GIP firms that combination accounts for (analogous to how common the pattern is). Combinations whose consistency clears a conventional threshold (0.75–0.80 for sufficiency; 0.90 for necessity) are retained as valid pathways; because several such combinations can pass this test at once, rather than the method picking a single best predictor, fsQCA can represent equifinality—the idea that different firms can reach the same outcome via different resource combinations—directly.

This study uses listed companies in China's A-share new energy sector as its research sample, specifically covering wind power, solar power, hydrogen energy, energy storage, and new energy equipment manufacturing. The new energy sector is central to energy-structure optimization, clean-energy substitution, and low-carbon technology upgrading, making it suitable for examining green innovation and digital transformation.

Considering that single-year data may be subject to short-term fluctuations, this study sets the research period from 2019 to 2023 and calculates the mean value of each variable over this period to enhance data stability and reliability. This five-year window was chosen because it is the most recent period for which digital-transformation text-analysis data, green patent records, and carbon-emission disclosures are simultaneously and consistently available for Chinese A-share new energy firms, and it spans a full "dual carbon" policy cycle following the 2020 announcement of China's carbon peak and carbon neutrality targets. The window necessarily includes the 2020–2022 COVID-19 period. Using period averages rather than single-year values is itself a partial safeguard against COVID-related short-term shocks, since transient disruptions to production or R&D spending in any one year are smoothed by the four other years; nevertheless, we acknowledge this as a limitation and return to it in Section 5.3. To ensure a balanced and comparable sample, only firms that were continuously listed and reporting throughout 2019–2023 were retained, that is,

firms that were delisted, suspended, or newly listed partway through the window were excluded rather than treated as entering or leaving the panel mid-period. During sample screening, this study excludes companies subject to ST or *ST treatment, companies with severe missing values for key variables, and samples with data anomalies. The detailed screening procedure is described below.

The sample-selection procedure followed four steps. First, we identified Chinese A-share listed firms whose principal business activities were directly related to the new energy sector, including wind power, solar power, hydrogen energy, energy storage, and new energy equipment manufacturing. Industry membership was determined by combining listed-company industry classifications, firms' principal business descriptions, and annual-report disclosures on major revenue sources. Second, firms that were subject to ST or *ST treatment during the study period were excluded, because their abnormal financial status may affect the comparability of innovation and resource-allocation behavior. Third, firms with serious missing values in key variables, including green patents, digital transformation, R&D intensity, government subsidies, and carbon-emission performance, were excluded. Fourth, observations with clearly abnormal or non-comparable data were removed. After these screening steps, the final balanced sample consisted of 54 Chinese A-share listed new energy enterprises over the 2019–2023 period.

To improve transparency without overloading the main text with a firm-by-firm list, we report the aggregate sample distribution. Among the 54 firms, 22 are state-owned enterprises, accounting for 40.7% of the sample, and 32 are non-state-owned enterprises, accounting for 59.3%. This composition indicates that the sample includes both SOEs and non-SOEs, allowing ownership structure to be treated as a conditional variable rather than as a sampling restriction.

Green patent data are sourced from the China National Intellectual Property Administration patent database; data related to digital transformation are obtained through text analysis of corporate annual reports; financial data are sourced from CSMAR; carbon emission performance data are sourced from corporate social responsibility reports, ESG reports, and relevant carbon emission databases; and government subsidy data are sourced from notes to corporate financial statements and the CSMAR database.

3.2. Variable Selection

3.2.1. Outcome Variable

This study uses the number of green patent grants (Y) as the outcome variable to measure GIP. Green patents capture a firm's documented technological output in areas such as energy conservation, emission reduction, clean energy, and pollution control, and are widely used to evaluate corporate green innovation [46–49]. We recognize two limitations of this choice. First, patent grants lag patent applications and the underlying R&D and resource-allocation decisions by one to several years, so grants observed within the 2019–2023 window partly reflect technological investments and digital or organizational resources committed before, rather than within, the window; using the 2019–2023 period average for both the outcome and the conditions mitigates but does not eliminate this timing mismatch. Second, as a count of granted output, this indicator captures the technological-output dimension of green innovation but not green process or green management innovation; patent-based indicators may underrepresent non-patented process, management, and incremental innovations, so the outcome should be interpreted as technological green innovation output rather than the whole universe of green innovation activity [48,49]. We revisit this limitation in Section 5.3.

We nonetheless use granted green patents, rather than a broader innovation index, because patent grant records are independently verified by a national patent office, are

available consistently across all 54 sample firms for 2019–2023, and are the most widely used objective (as opposed to self-reported or survey-based) indicator in this literature [46–49]; we recognize that a substantial share of incremental process and management innovation is never patented, and note this as an interpretive boundary on our findings rather than a flaw specific to this study.

3.2.2. Conditional Variables

1. Level of Digital Transformation (DIG). Digital transformation measures the depth and breadth of a firm's digital technology application. This study constructs the indicator through text analysis of annual reports by calculating the frequency of terms related to big data, cloud computing, artificial intelligence, the Industrial Internet, and blockchain. A higher value indicates deeper integration of digital technologies into business processes [50]. We recognize that digital transformation is a multi-faceted construct spanning technology (e.g., cloud computing, AI, cybersecurity), people and culture (workforce mindset and digital literacy), and process (redesigning workflows rather than merely digitizing them), and that our text-frequency measure primarily captures the technology-disclosure facet—firms' stated adoption of specific digital technologies—rather than the culture or process dimensions. We adopt it nonetheless because it is constructed from a standardized, independently auditable public disclosure (annual reports) available for all sample firms, and because it is the most widely used comparable proxy for digital transformation intensity in the Chinese listed-firm literature [50]; we note the resulting narrowing of construct coverage as a limitation revisited in Section 5.3. The five keyword categories used here (big data, cloud computing, artificial intelligence, Industrial Internet, blockchain) follow the digital-technology dictionary applied in the source cited above [50]. The underlying text-processing procedure follows the "search–match–sum" method established by Wu et al. [51], who extracted the full text of Chinese A-share listed firms' annual reports, matched this text against the digital-transformation keyword dictionary, and aggregated matched-keyword frequencies at the firm level; consistent with their approach, and with the right-skewed distribution they document for this measure, the resulting raw counts are log-transformed before entering the calibration step. Word frequencies are computed at the firm level and then averaged over the 2019–2023 period along with the other conditions, consistent with the period-averaging approach described in Section 3.1. We did not conduct a separate validity check against an independent digitalization index for the present sample; this remains flagged as a limitation for future work.
2. R&D Intensity (RDI). RDI measures a firm's investment in technological innovation, expressed as the ratio of average annual R&D expenditure to operating revenue. Higher RDI reflects stronger technological resource input and innovation capability.
3. Firm Size (SIZE). Firm size reflects a firm's resource base and organizational capacity, measured by the natural logarithm of average annual total assets. Larger firms usually have stronger financial resources, more mature management systems, and greater capacity to support green innovation.
4. Ownership Structure (SOE). Ownership structure distinguishes whether a firm is state-controlled. SOEs are assigned a value of 1, while non-SOEs are assigned a value of 0. The 54-firm sample includes both SOEs and non-SOEs rather than SOEs alone; ownership structure is analyzed as one of the six conditions precisely so that its role can vary across configurations rather than being assumed. In China's institutional context, state-owned new energy enterprises often face stronger policy responsibilities and incentives for green innovation reflecting the social (S) dimension of SOE status:

as agents of state industrial policy, SOEs are typically subject to closer government oversight, carbon-reduction mandates, and reporting obligations than private firms, which can both motivate green innovation and expose the resulting patent output to a degree of political and policy influence rather than market incentives alone. Because government subsidies (SUB) and carbon regulation pressure are themselves partly channeled through ownership status, some of the association between SOE status and GIP identified in the configurational results may reflect political or policy alignment rather than purely resource-based advantages; we flag this possibility explicitly in the interpretation of the SOE-related pathways in Section 4 and revisit it as a limitation in Section 5.3.

5. Government Subsidies (SUB). Government subsidies measure external institutional support, expressed as the natural logarithm of the average annual amount of subsidies received. Subsidies can reduce the costs and risks of green R&D and encourage firms to increase green innovation investment.
6. Carbon Emission Performance (CARB). Carbon emission performance measures a firm's ability to reduce emissions and improve low-carbon operational efficiency. It is expressed as the reciprocal of total carbon emissions per 1 million yuan of net sales. A higher value indicates lower emissions per unit of sales revenue and stronger low-carbon governance capability [52]. We draw the underlying emissions data from corporate social responsibility reports, ESG reports, and carbon emission databases (Section 3.1), but CARB itself operationalizes only the environmental (E) dimension of ESG—carbon intensity of sales—rather than a composite ESG score. The social (S) and governance (G) dimensions of ESG are not modeled as separate conditions in this study: SOE status (see below) captures part of the governance and social-responsibility profile associated with state ownership, while broader S and G considerations lie outside the technological–organizational–institutional resource framework adopted here and are noted as an avenue for future research in Section 5.3.

The variable descriptions are shown in Table 1.

Table 1. Variable Descriptions.

Variable Type	Variable Name	Symbol	Measurement Method
Outcome variable	Green Innovation Performance	Y	Number of green patents granted during the study period
Conditional variables	Level of Digital Transformation	DIG	Word frequency of digital technology terms (big data, cloud computing, AI, Industrial Internet, blockchain) in annual reports
	R&D Intensity	RDI	Ratio of average annual R&D expenditure to operating revenue
	Firm Size	SIZE	Natural logarithm of average annual total assets
	Ownership Structure	SOE	SOEs = 1; non-SOEs = 0
	Government Subsidies	SUB	Natural logarithm of average annual government subsidies received
	Carbon Emission Performance	CARB	Reciprocal of total carbon emissions per 1 million yuan of net sales; higher values indicate stronger low-carbon governance

To provide the descriptive and distributional information requested, Table 2 reports descriptive statistics and Table 3 reports the Pearson correlation matrix for the seven original (pre-calibration) variables across the 54 sample firms.

Table 2. Descriptive Statistics of Original Variables (n = 54).

Variable	Mean	SD	Min	25th Pct.	Median	75th Pct.	Max
PATG	11.956	12.423	0.200	3.100	7.500	18.450	51.400
DIG	5.496	5.961	0.000	1.650	3.500	7.650	29.000
RDI	3.722	2.661	0.066	1.754	3.541	4.720	11.140
SIZE	23.165	1.198	20.953	22.194	23.232	23.791	25.690
SOE	0.407	0.496	0.000	0.000	0.000	1.000	1.000
CARB	1.103	0.349	0.436	0.839	1.080	1.255	2.608
SUB	16.453	1.248	13.159	15.629	16.327	17.184	19.756

Note: PATG, DIG, RDI, CARB, and SUB are measured in their original (raw) units before calibration; SIZE is log-transformed firm size; SOE is a binary indicator (1 = state-owned).

Table 3. Correlation Matrix of Original Variables (Pearson, n = 54).

	PATG	DIG	RDI	SIZE	SOE	CARB	SUB
PATG	1.000						
DIG	0.199	1.000					
RDI	−0.106	0.256	1.000				
SIZE	0.648	−0.164	−0.467	1.000			
SOE	0.334	−0.178	−0.380	0.502	1.000		
CARB	−0.088	0.164	0.328	−0.264	−0.320	1.000	
SUB	0.502	0.107	0.114	0.451	0.102	−0.104	1.000

Note: values are Pearson correlation coefficients among the seven original (pre-calibration) variables; the upper triangle is omitted by symmetry.

3.3. Variable Calibration

Prior to conducting fsQCA, original variables must be calibrated into fuzzy-set membership scores ranging from 0 to 1. This study adopts the direct calibration method following Ragin and Fiss. Since the selected variables lack unified external thresholds, the 25th, 50th, and 75th percentiles of the sample data are used as the full non-membership, crossover, and full membership anchors, respectively [41–45]. Continuous variables are calibrated accordingly, while ownership structure is treated as a binary variable, with SOEs assigned 1 and non-SOEs assigned 0. The calibration anchors are shown in Table 4. Concretely, for each variable the 25th percentile of the 54 sample values is set as the full non-membership anchor (score 0), the 50th percentile (median) as the crossover anchor (score 0.5, the point of maximum ambiguity), and the 75th percentile as the full membership anchor (score 1); values between anchors are interpolated using the standard logistic transformation (log-odds = 3 × (raw value − crossover)/(nearest anchor − crossover), converted to a 0–1 score via the logistic function). For example, Table 4 sets DIG's three anchors at 1.65, 3.50, and 7.65; a firm with a raw DIG score of 5.50 lies between the crossover (3.50) and full-membership (7.65) anchors, giving a log-odds of $3 \times (5.50 - 3.50)/(7.65 - 3.50) \approx 1.45$ and a calibrated fuzzy membership of $\exp(1.45)/(1 + \exp(1.45)) \approx 0.81$ in the "high digital transformation" set. We use sample percentiles rather than externally fixed, theoretically grounded anchors because none of the six conditions in this study has a generally accepted external benchmark for what counts as "high" or "low" (unlike, for example, a regulatory capital-adequacy ratio with a fixed legal threshold). Under these conditions, sample-relative percentile anchors are a calibration strategy commonly used in fsQCA research on medium-n samples where no external standard exists [41–45]. The corresponding trade-off, which we note explicitly, is that calibration is sample-dependent: the resulting membership scores indicate whether a firm is high or low relative to this specific sample of 54 new energy enterprises, not against an absolute or cross-industry standard, and we flag this as a boundary condition on generalizability in Section 5.3.

Table 4. Calibration Anchors for Each Variable.

Variable Category	Variable	Full Non-Membership	Crossover Point	Full Membership	Calibration Target Set Meaning
Outcome variable	Y	3.1000	7.5000	18.4500	"High GIP" set
Conditional variables	DIG	1.6500	3.5000	7.6500	"High Digital Transformation Level" set
	RDI	1.7540	3.5410	4.7195	"High RDI" set
	SIZE	22.1941	23.2321	23.7915	"Large Firm Size" set
	CARB	0.8385	1.0797	1.2555	"High Carbon Emission Performance" set
	SUB	15.6287	16.3271	17.1838	"High Government Subsidies" set
	SOE	0	—	1	"SOEs" set

3.4. Necessary Condition Analysis

Before conducting the configurational analysis, this paper first examines whether each antecedent condition constitutes a necessary condition for high GIP. We report this necessary-condition check here, ahead of the main configurational results in Section 4, because it is a required diagnostic step within the fsQCA procedure itself (per the four-step workflow outlined in Section 3.1) rather than a substantive finding in its own right; readers interested primarily in the sufficiency results may proceed directly to Section 4. According to the standard criteria in fsQCA research, an antecedent condition is considered necessary only when its consistency reaches or exceeds 0.90. This study uses Y_fz as the outcome variable and conducts necessary condition analysis on all six conditions. The results are shown in Table 5. Consistency and coverage here are computed set-theoretically rather than through hypothesis testing: for a necessity test of condition X on outcome Y, consistency = Σmin(X_i, Y_i) / ΣY_i measures the proportion of a firm's membership in the outcome (Y) that is also covered by its membership in the condition (X)—that is, whether firms with high GIP also tend to have high values on the condition, which is what a necessity claim requires—while coverage = Σmin(X_i, Y_i) / ΣX_i measures what share of the condition's membership is in turn accounted for by the outcome, an indicator of empirical relevance rather than of necessity itself. For example, Table 5 reports a DIG_fz consistency of 0.621 and coverage of 0.596, meaning that about 62% of firms' membership in "high GIP" is also covered by their membership in "high digital transformation," while about 60% of firms' membership in "high digital transformation" is in turn covered by "high GIP"—well below the 0.90 consistency threshold required to treat DIG alone as a necessary condition.

Table 5. Results of Necessary Condition Analysis Based on fsQCA.

Antecedent Condition	Y_fz Consistency	Y_fz Coverage
DIG_fz	0.621	0.596
RDI_fz	0.535	0.487
SIZE_fz	0.769	0.699
CARB_fz	0.522	0.475
SUB_fz	0.710	0.649
SOE_fz	0.516	0.589

As shown in Table 5, the consistency of each antecedent condition is below 0.90, indicating that no single factor constitutes a necessary condition for high GIP. This confirms

that GIP in new energy enterprises emerges from multiple conjunctural causation rather than single-condition determinism, consistent with a complex systems perspective.

Among the antecedents, firm size (SIZE_fz = 0.769) and government subsidies (SUB_fz = 0.710) show relatively higher consistency values, indicating the importance of scale resources and policy support. Digital transformation (DIG_fz = 0.621) is an important enabling factor but not a necessary condition on its own. Overall, high GIP results from the combined effects of multiple resources and capabilities, consistent with RBV's emphasis on resource combination and synergy. Further, a sufficient condition for configurational analysis is therefore needed to identify the resource allocation pathways leading to high GIP.

4. Discussion

To further reveal the multiple pathways through which digital transformation is associated with high GIP in new energy enterprises, this study employs fsQCA to conduct sufficient condition configurational analysis. This study uses the intermediate solution as the primary basis for interpreting configurational pathways and combines it with the parsimonious solution to identify core and peripheral conditions. The specific results are shown in Table 6. In presenting these results, we distinguish between what the fsQCA results directly establish—that a given combination of conditions is sufficient (and, per the robustness test in Section 4.3, reasonably stable) for high GIP—and our substantive interpretation of why each combination works, which draws on RBV and systems logic but is not itself directly tested by the configurational analysis; we flag this distinction explicitly where relevant below and revisit it in Section 5.3. For transparency and replicability, the truth table construction should be reported in full, including: the case-frequency threshold applied (i.e., the minimum number of empirical cases required for a configuration to be coded, commonly set to 1 in medium-*n* samples such as this one); the raw consistency threshold used to code a configuration as sufficient (the results in Table 6 are consistent with a threshold at or below 0.834, the lowest configuration-level consistency reported there); whether PRI (proportional reduction in inconsistency) consistency was also checked, and at what threshold, to screen out configurations subject to simultaneous subset relations; and whether directional expectations were specified for the counterfactual analysis underlying the intermediate solution, or whether the standard fsQCA default (relying only on the easy counterfactuals implied by the necessity analysis in Section 3.4) was used instead. This study applied a case-frequency threshold of 1, a raw consistency threshold of 0.80, and a PRI consistency threshold of 0.70 in constructing the truth table, consistent with the raw truth-table rows underlying the six reported configurations, all of which clear these cutoffs. Directional expectations were specified as "present" for DIG, RDI, SIZE, CARB, and SUB—each theoretically expected to favor high GIP—while SOE was left undirected, given the mixed theoretical expectations for ownership structure discussed in Section 3.2.

Overall, there is no single optimal path for achieving high GIP in new energy enterprises; rather, the results reveal a distinct pattern of multiple conjunctural causation and coexisting equivalent pathways, consistent with a complex adaptive systems perspective in which equifinality is a hallmark of system behavior. Digital transformation appears in five of the six configurational pathways, indicating that it is a key enabling condition. However, digital transformation does not function as an isolated system element; it requires synergistic alignment with RDI, firm size, carbon emission performance, government subsidies, and ownership structure. The key to the digital empowerment of green innovation lies not simply in whether enterprises pursue digital transformation, but in whether digital capabilities can be effectively embedded within firms' technological investment, resource base, low-carbon governance, and institutional support systems.

Table 6. QCA Results for High GIP.

Conditional Variables	H1a	H2a	H1b	H2b	H1c	H2c
DIG	▲		▲	▲	●	▲
RDI	▲			▲		▽
SIZE		●		▲	▲	▲
CARB			▽	▲	●	▽
SUB		●	▲			▲
SOE	▲	●	▲		●	
Original coverage	0.119	0.299	0.145	0.212	0.102	0.124
Unique coverage	0.023	0.161	0.020	0.145	0.039	0.040
Consistency	0.958	0.834	0.919	0.925	0.966	0.871
Overall coverage	0.597					
Overall consistency	0.882					

Note: ● indicates the presence of a core condition; ▲ indicates the presence of a peripheral condition; ▽ indicates the absence of a peripheral condition; a blank indicates that the condition is optional in that configuration. Core conditions (circle symbols) and peripheral conditions (triangle symbols) use deliberately different shapes, rather than dot size alone, to make them easier to distinguish at a glance. Core conditions appear in both the parsimonious solution and the intermediate solution; peripheral conditions appear only in the intermediate solution. The column headings H1a, H1b, H1c, H2a, H2b, and H2c are configuration identifiers (matching the Config. ID column in Table 7 and the labels used throughout Section 4), not numbered hypotheses; no hypotheses of this kind are formulated elsewhere in this paper.

Table 7. Summary of Configurational Pathway Types for High GIP.

Config. ID	Theoretical Label	Core Logic
H1a	SOE Digital–R&D Synergy	SOEs convert digital transformation and R&D investment jointly into high GIP
H1b	SOE Digital–Subsidy Compensation	In SOEs, digital transformation and subsidies compensate for weak carbon performance
H1c	SOE Digital–Scale–Carbon Synergy	Large SOEs combine digital, scale, and low-carbon governance strengths for high GIP
H2a	Scale–Subsidy Support (no digital transformation)	SOEs reach high GIP via scale and subsidies alone, without digital transformation
H2b	Internal Capability Synergy (digital—independent of ownership/subsidy)	Digital, R&D, scale, and carbon capabilities jointly drive GIP regardless of ownership
H2c	Digital–Scale–Subsidy Substitution	Digital transformation, scale, and subsidies substitute for weak R&D and carbon performance

Table 7 synthesizes the six pathways according to their resource-allocation characteristics. Based on the core resource logic of each pathway, this paper classifies the six pathways into two categories: the "SOE digital-empowerment-driven pathway," characterized by the synergy between SOE resource base and digital capabilities (H1a, H1b, H1c); and the "resource–capability synergy and substitution pathway," based on scale resources, R&D investment, and policy support (H2a, H2b, H2c). To make these configurations more concrete, each can be associated with a stylized firm archetype (illustrative composites consistent with the configuration's defining conditions, not descriptions of specific named firms in our sample): H1a resembles a state-owned new energy enterprise that pairs heavy digital investment with sustained R&D spending; H1b resembles a subsidized SOE whose digital capability sustains high GIP despite comparatively weak carbon-performance scores; H1c resembles a large SOE combining digital, scale, and low-carbon governance strengths; H2a resembles a large, subsidized SOE that reaches high GIP through scale and policy resources without digital transformation as a contributing condition; H2b resembles a firm, regardless of ownership, whose internal digital, R&D, scale, and carbon-governance capabilities are jointly strong enough that ownership and subsidies are not part of the suffi-

cient combination; and H2c resembles a firm that substitutes scale, subsidies, and digital transformation for comparatively weaker R&D and carbon performance. We emphasize that these are archetypal illustrations of what each configuration implies substantively, not case studies of individual firms; a firm-level qualitative case analysis was outside the scope of the present fsQCA design and is a natural direction for future research. It is also worth noting that unique coverage—the share of high-GIP cases explained by a configuration alone, net of overlap with the other five—varies considerably across the six pathways: Table 6 reports values ranging from 0.020 (H1b) and 0.023 (H1a) up to 0.161 (H2a), with the remaining configurations falling between these extremes (H2b = 0.145, H2c = 0.040, H1c = 0.039). Low unique coverage does not mean a pathway is unimportant or spurious: each configuration still clears the sufficiency consistency threshold on its own terms (Table 6), and low unique coverage instead indicates that the cases it explains substantially overlap with cases also explained by other configurations, that is, some firms satisfy more than one sufficient pathway at once. We therefore treat unique coverage as an indicator of how empirically distinctive a pathway is within this sample, rather than as a measure of its theoretical importance. Figure 2 presents the two pathway clusters and six configurations leading to high GIP.

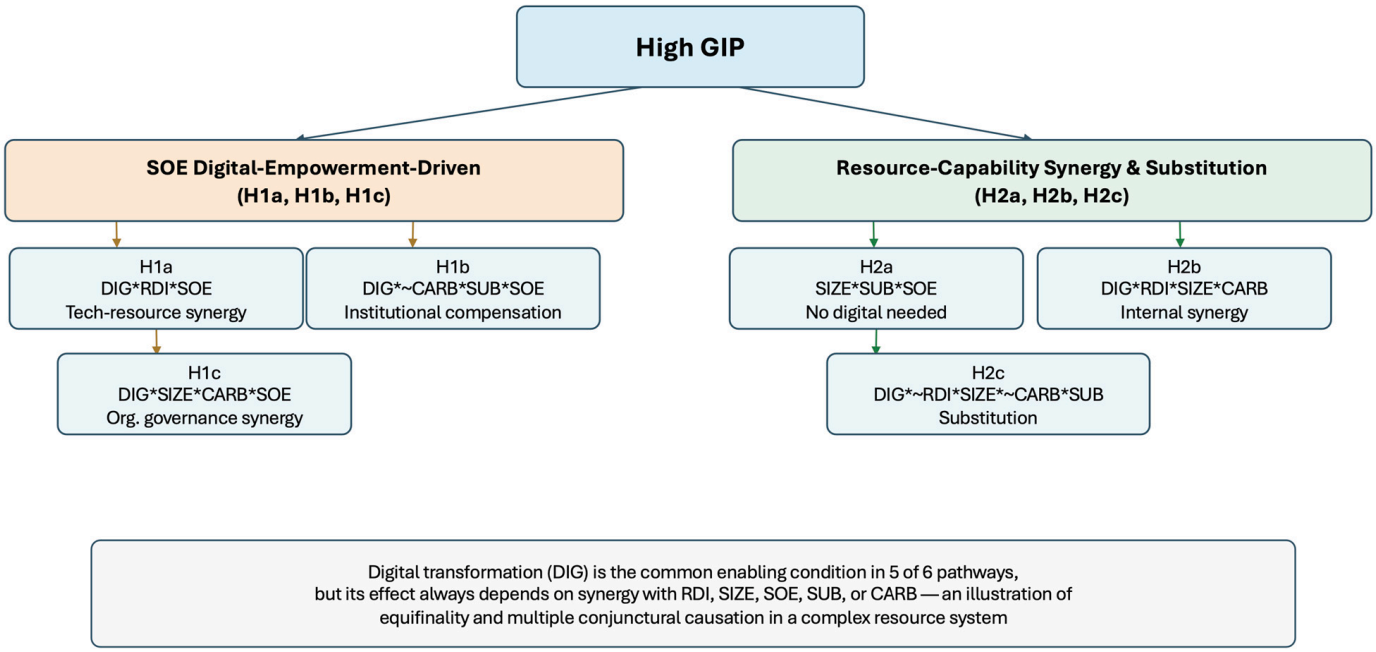


Figure 2. The two pathway clusters and six configurations leading to high GIP.

4.1. SOE Digital-Empowerment-Driven Pathway

Configuration H1a indicates that, within state-owned new energy enterprises, high digital transformation combined with high RDI is jointly sufficient for high GIP. The pathway shows that SOE ownership advantages translate into GIP only when combined with digital capabilities and R&D investment. From an RBV perspective, digital transformation constitutes a critical heterogeneous technological resource that enhances R&D management efficiency, information processing, and innovation synergy, enabling R&D investment to be more effectively converted into green innovation outputs. State-owned new energy enterprises typically possess strong policy responsiveness, resource access, and long-term strategic execution capacity. Building upon this organizational resource foundation, the synergistic combination of digital capabilities and R&D investment forms a three-pronged green innovation-driving mechanism: "digital capabilities–technological investment–SOE resources."

Configuration H1b indicates that among state-owned new energy enterprises, even in the absence of favorable carbon emission performance, high GIP can still be achieved with a high level of digital transformation and strong government subsidy support. This result reveals a "resource compensation mechanism" enabled by digitalization. For SOEs whose low-carbon governance performance has not yet reached a high level, digital transformation can compensate for low-carbon shortcomings by improving energy management, production scheduling, operational monitoring, and resource allocation efficiency; government subsidies, as external institutional resources, reduce the financial constraints and risk costs associated with green innovation. The synergistic effect of these two resource types enables firms to sustain high GIP even where carbon emission performance is insufficient, reflecting the resource complementarity and substitutability logic emphasized by RBV and complementarity theory [53]. We note that fsQCA establishes that this combination of conditions is sufficient for high GIP; it does not, by itself, test whether digital transformation operates through the specific operational channels (energy management, production scheduling, monitoring, resource allocation) suggested above. That mechanism-level account is our theoretical interpretation of why the co-occurrence in configuration H1b is plausible, offered as a candidate explanation for future process-level or mediation research to test directly, rather than as a finding directly established by the configurational results themselves.

Configuration H1c indicates that for state-owned new energy enterprises, the synergy among high digital transformation, large firm size, and high carbon emission performance forms an effective pathway to high GIP without requiring high RDI or high government subsidies. This suggests that some large state-owned new energy enterprises can achieve GIP improvements by leveraging existing organizational scale advantages, low-carbon governance foundations, and digital management capabilities. The underlying resource logic is as follows: large-scale enterprises possess stronger resource allocation capabilities, organizational coordination capabilities, and technical application scenarios, providing a stable organizational resource foundation for digital transformation and green innovation; higher carbon emission performance indicates accumulated low-carbon governance experience, enabling further transformation of green management capability into green technological innovation; digital transformation integrates and connects these organizational resources and governance capabilities, forming a stable green innovation-driven mechanism.

A synthesis of H1a, H1b, and H1c reveals that high GIP in state-owned new energy enterprises requires flexible combinations of digital transformation with differentiated conditions rather than reliance on a single resource advantage. H1a embodies a "technological resource synergy logic" (digital transformation + R&D investment); H1b embodies an "institutional resource compensation logic" (digital transformation + government subsidies); H1c embodies an "organizational resource governance synergy logic" (digital transformation + firm size + carbon emission performance). These configurations show that digital transformation plays different enabling roles depending on R&D foundations, institutional resources, and low-carbon governance. From an RBV perspective, the common feature across these pathways is that digital transformation constitutes a key technological resource; SOE status and firm size provide the organizational resource foundation; and RDI, government subsidies, and carbon emission performance, respectively, enhance the overall resource allocation efficiency at the levels of technological investment, external institutional resources, and low-carbon governance.

4.2. Resource–Capability Synergy and Substitution Pathways

Configuration H2a indicates that, among state-owned new energy enterprises, a combination of large firm size and high government subsidies is similarly sufficient for

high GIP. Digital transformation does not appear in this pathway, suggesting that under specific resource conditions, new energy enterprises can achieve GIP improvements through scale resources, external policy support, and ownership advantages without requiring digital transformation as a prerequisite. This finding supports the equifinality result rather than diminishing the role of digital transformation. From an RBV perspective, large-scale SOEs inherently possess substantial financial resources, technological reserves, and organizational execution capabilities; government subsidies reduce the uncertainty and cost pressures associated with green innovation; combined with the strong policy responsiveness of SOEs, these factors form a green innovation support pathway dominated by "organizational resources + institutional resources."

Configuration H2b best embodies the logic of "digital empowerment of internal capability synergy." The combined effects of high digital transformation, high RDI, large firm size, and high carbon emission performance are jointly sufficient for new energy enterprises to achieve high GIP without depending on ownership structure or government subsidies. This demonstrates that, when a firm possesses a strong foundation of internal resource capabilities, it can achieve green innovation breakthroughs through the synergistic integration of its own resources. The underlying mechanism is as follows: digital transformation enhances a company's dynamic perception and control over R&D, production, supply chains, and energy utilization; RDI provides sustained investment for green technological innovation; firm size offers the resource foundation and application scenarios for innovation activities; and high carbon emission performance indicates solid low-carbon governance experience and green operational foundations. The organic integration of these four resource types forms a highly synergistic internal driving mechanism—"digital capabilities–technological investment–scale resources–low-carbon governance"—a concentrated manifestation of the heterogeneous resource combination advantages emphasized by RBV.

Configuration H2c reveals an alternative driving logic. Even where RDI is insufficient, and carbon emission performance has not yet reached a high level, firms can still achieve high GIP with high digital transformation, substantial firm size, and strong government subsidy support. Consistent with complementarity and fit arguments, this reveals diverse mechanisms for resource substitution and compensation [53]: when RDI is weak, digital transformation can mitigate innovation constraints through improved resource allocation efficiency, technology search capabilities, and organizational coordination; when carbon emission performance is inadequate, government subsidies intervene as external institutional resources, reducing green transformation costs and guiding enterprises toward green technology upgrades; firm size provides the necessary resource capacity for digital system development, green technology application, and commercialization of innovation outcomes. H2c thus demonstrates a substitute-driven mechanism in which "digital capabilities + scale foundation + external institutional resources" synergistically compensate for internal resource deficiencies.

Together, H2a, H2b, and H2c show that high GIP can arise either from internal capability synergies or from support and substitution involving scale resources and policy subsidies. In H2a, scale and institutional resources are directly sufficient for GIP without digital transformation; in H2b, digital transformation forms a high degree of internal synergy with RDI, scale resources, and carbon emission performance; in H2c, digital transformation combines with scale resources and government subsidies to compensate for deficiencies in RDI and low-carbon performance. From an RBV perspective, the common features across these pathways are that firm size provides the organizational resource foundation for green innovation; RDI and digital transformation together constitute technological resource sources; and government subsidies play a compensatory institutional resource role in certain contexts. The three types of resources form different synergy

and substitution configurations based on firm endowment differences, consistent with the idea that the value of one strategic element depends on its fit with other elements in the system [53].

4.3. Robustness Test

To test robustness, this study raises the raw consistency threshold used to construct the truth table from 0.80 (the baseline threshold used in Section 4) to 0.85, while retaining the PRI consistency threshold of 0.70, and then re-runs the analysis under this stricter cutoff. At this level, exactly one baseline configuration drops below the sufficiency bar, while the other five remain intact, consistent with the six-to-five reduction reported here. The baseline analysis (Section 4, Table 6) produced an overall solution consistency of 0.882 and overall coverage of 0.597 across six configurations. Under the stricter screening condition, the number of configurational pathways leading to high GIP decreases from six to five, with overall coverage of 0.453 and overall consistency rising to 0.931, indicating that the retained pathways exhibit higher explanatory consistency.

As shown in Table 8, the robustness test results still involve digital transformation, RDI, firm size, carbon emission performance, government subsidies, and ownership structure. Notably, digital transformation appears in all five robust pathways, while other conditions play varying roles across configurations.

Table 8. Robustness Test Results.

Conditional Variables	R1	R2	R3	R4	R5
DIG	▲	▲	▲	▲	▲
RDI	▲		▽	▲	
SIZE			▲	▲	▲
CARB				▲	▲
SUB		▲	▲		
SOE	▲	▲			▲
Original coverage	0.119	0.169	0.161	0.212	0.102
Unique coverage	0.012	0.020	0.057	0.127	0.039
Consistency	0.958	0.922	0.894	0.925	0.966
Overall coverage	0.453				
Overall consistency	0.931				

Note: ▲ indicates the presence of a condition; ▽ indicates the absence of a condition; a blank indicates that the condition is optional in that robustness configuration. Unlike Table 6, this robustness table reports retained solution terms only and does not distinguish core from peripheral conditions.

Compared with the baseline analysis, some pathways with low coverage or relatively weak consistency are excluded, but the main configurational logic does not undergo substantial changes. In particular, pathways such as "digital transformation–R&D capability–ownership structure," "digital transformation–RDI–firm size–carbon emission performance," and "digital transformation–firm size–carbon emission performance–ownership structure" remain stable, supporting the robustness of this paper's configurational conclusions regarding digital transformation and high GIP in new energy enterprises.

5. Recommendations and Conclusions

5.1. Policy Recommendations

The fsQCA results indicate that high GIP depends on coordinated resources rather than a single factor. Accordingly, this study proposes the following policy implications.

First, new energy enterprises should build a synergistic mechanism between digital transformation and R&D capabilities. Digital transformation should not be limited to information system upgrades or business process digitization, but should deeply integrate

digital technologies into green R&D, production management, clean production, and low-carbon governance [54,55]. Enterprises with strong R&D foundations should promote the integration of digital tools with green technology development through digital twins, intelligent monitoring, and collaborative R&D platforms. Firms with weaker RDI should use digital tools to improve resource allocation and technology search capabilities, gradually strengthening green innovation capacity [54,55]. State-owned new energy enterprises should integrate digital capabilities with R&D investment, low-carbon governance, and policy response mechanisms, while private enterprises should use flexible digital platforms and open innovation tools to enhance agility and reduce green innovation costs.

Second, a support mechanism linking scale resources and policy support should be established. Since green innovation is capital-intensive, technology-intensive, and long-term oriented, large firms should transform scale advantages into green R&D budgets, green patent portfolios, low-carbon technology upgrades, and digital management capabilities rather than merely expanding production capacity. Governments should improve the precision and continuity of subsidy policies, aligning support with firms' digital transformation foundations, green R&D investment levels, carbon emission performance improvements, and green innovation outputs [56]. For firms with sound digital foundations but insufficient RDI, targeted subsidies, green credit, and tax incentives can strengthen R&D capabilities. For firms with weak carbon emission performance but clear transition potential, subsidies should guide investment toward energy conservation, carbon reduction, and green technology upgrading. A performance evaluation mechanism should also assess the effectiveness of subsidies in promoting green innovation, digital application, and carbon performance improvement.

Third, a multi-stakeholder green innovation ecosystem should be developed. Since high GIP depends on the dynamic alignment of multiple resources rather than isolated firm-level action, policy efforts should extend from individual enterprises to the coordination of industrial chains, innovation chains, and policy chains [57,58]. At the enterprise level, firms should select green innovation pathways according to their resource endowments and development stages. At the policy level, differentiated tools should be adopted for different types of firms: large SOEs should be encouraged to undertake key green technology projects, while growing private firms should receive flexible financial support, R&D subsidies, and digital transformation services [57,58]. At the systemic level, collaboration among governments, enterprises, research institutions, financial institutions, and upstream and downstream partners should be strengthened, so that green technologies, digital capabilities, and policy resources flow more efficiently across the new energy sector, enabling digital transformation to function not merely as a firm-level management tool but as a systemic driver of green innovation and high-quality development across the industry.

To make these recommendations more directly actionable, we map them onto the six configurations identified in Section 4. Firms whose profile resembles H1a or H2b are best positioned to pursue the first recommendation above, deepening the integration of digital tools with R&D activity, since digital and R&D capability are already jointly present in their resource base. Firms resembling H2a, which reach high GIP through scale and subsidies without digital transformation as a contributing condition, should treat the second recommendation—converting scale and subsidy resources into digital and green R&D capacity—as a priority, since their current pathway does not yet draw on digital resources at all. Firms resembling H1b or H2c, which combine digital transformation and subsidies with comparatively weaker carbon performance or R&D, should use that existing digital-subsidy synergy as a base from which to specifically target their weaker condition (carbon governance or R&D, respectively), consistent with the subsidy-targeting guidance in the second recommendation. Firms resembling H1c already combine digital, scale, and

carbon-governance strengths and are better positioned to serve as the large-SOE anchors for the sector-level coordination described in the third recommendation.

5.2. Conclusions

This study adopts the RBV as its theoretical framework and employs fsQCA to examine the configurational pathways through which digital transformation is associated with high GIP in Chinese A-share listed new energy enterprises.

The results indicate that none of the individual conditions constitutes a necessary condition for high GIP, suggesting that GIP in new energy enterprises is characterized by multiple conjunctural causation rather than single-factor determinism. High GIP is an emergent property of complex interactions among technological, organizational, and institutional resources, consistent with a systems perspective. The configurational analysis identifies six equivalent pathways, summarized into two typical models: the "SOE digital-empowerment-driven pathway" and the "resource–capability synergy and substitution pathway." Digital transformation appears in five of the six pathways, suggesting that it is an important enabling condition, but its effect depends on alignment with R&D resources, organizational scale, low-carbon governance capability, government support, and ownership characteristics. From the RBV perspective, the value of digital transformation lies not simply in improving the level of digitalization itself, but in enabling the integration and complementary allocation of heterogeneous resources, thereby continuously improving GIP in new energy enterprises. The specific, non-obvious contribution of this study is thus twofold: theoretically, it shows that RBV's resource-complementarity logic and a systems perspective are mutually reinforcing when operationalized through fsQCA–resource combination is not a metaphor but an empirically identifiable configuration; practically, it replaces the generic prescription "invest in digital transformation" with six named, falsifiable resource recipes (H1a–H1c, H2a–H2c) that a manager or policymaker can match to a specific firm's ownership status, scale, R&D intensity, and carbon-governance starting point. To be precise about what is genuinely new here: relative to existing RBV research, the increment is not a new construct but a new mode of operationalization, treating resource complementarity, long a qualitative claim in RBV, as an empirically testable configurational property; relative to existing fsQCA research, this study does not extend the method itself, but demonstrates its use as an empirical strategy for adjudicating between competing resource-based explanations in a substantive domain (new energy enterprises' green innovation) where net-effect evidence has been inconclusive. We emphasize that the compensation and substitution relationships described among these pathways (e.g., digital transformation compensating for weak carbon governance in H1b, or for weak R&D in H2c) are our RBV-grounded interpretation of the configurational patterns rather than causal mechanisms directly demonstrated by fsQCA; readers should treat these as plausible, testable explanations rather than established findings. Two scope conditions bound these conclusions and the policy implications that follow. First, the sample comprises 54 listed Chinese A-share new energy enterprises observed over 2019–2023; the configurations identified describe pathways to high GIP within this specific institutional and sectoral context; and we do not claim that the same six pathways generalize to non-listed firms, to new energy enterprises outside China, or to other national systems of subsidy and ownership. Second, because GIP is operationalized here solely through granted green patents, our conclusions speak specifically to high green technological (patent) innovation output and should not be read as claims about green management innovation, green process innovation, environmental performance more broadly, or the commercialization of green technologies, each of which may follow a different configurational logic. The policy recommendations above should be read subject to both scope conditions.

5.3. Limitations

This study has several limitations. First, regarding sample selection, this study focuses on new energy enterprises listed on China's A-share market, which limits the scope of coverage. Caution should be exercised when generalizing findings to non-listed new energy enterprises or to other countries and regions. Relatedly, the final sample of 54 firms, while balanced across the 2019–2023 window, is not evenly distributed across ownership types and new energy sub-sectors; SOEs and larger, more capital-intensive firms are disproportionately represented among the pathways identified, so the "SOE digital-empowerment-driven" cluster in particular should be read as a pattern most representative of well-resourced, policy-embedded incumbents rather than of the new energy sector as a whole, and results for smaller or non-SOE firms warrant separate scrutiny in future work. Second, this study uses green patent grants as the sole measure of GIP, which primarily reflects the output dimension of green technological innovation and cannot fully capture green process innovation, green management innovation, or other dimensions, nor does it capture the social or governance dimensions of ESG performance discussed in Section 3.2. Future research could develop a more comprehensive GIP measurement system. Third, due to limitations in data availability, this study could not incorporate potential influencing factors such as entrepreneurial orientation, executive team characteristics, and technology cooperation networks, which may result in some degree of omitted variable bias. Fourth, because the analysis relies on historical, backward-looking data averaged over 2019–2023, the configurations identified describe the resource combinations that were associated with high GIP during this specific window rather than a validated predictive model; whether the same pathways will hold as digital technologies, subsidy regimes, and carbon policy continue to evolve is an open question. Future research could employ panel data regression, out-of-sample testing, or machine learning methods to cross-validate and extend the predictive capacity of the findings reported here.

As a further check on empirical credibility, future work could re-run the calibration with alternative anchor choices (e.g., 20th/50th/80th or 10th/50th/90th percentiles in place of 25th/50th/75th) and, where feasible, re-estimate GIP using an alternative or supplementary measure of green innovation (e.g., green patent applications in addition to grants, or a composite index incorporating green management or process innovation) to assess whether the six configurations and two pathway clusters identified here are stable across these alternative specifications. We leave these additional sensitivity analyses to future research.

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