Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Innovation performance at the intersection of technology, organization, and environment: A dynamic configurational analysis of Chinese new energy vehicle industry

Long Shi
Youjiang Medical University For Nationalities
Shuhua Li
Hezhou University
Xinshu Feng
Guangzhou Xinhua University
Lanhui Su
Guangxi University
Zhixin Guo
Nanning Normal University
Caisheng Liao
lcsmwill@foxmail.com
Kanazawa University

Article

Keywords: Panel data, New energy industry, Technology-organization-environment theory, Innovative performance

Posted Date: August 21st, 2025

DOI: https://doi.org/10.21203/rs.3.rs-7115926/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

With the accelerated advancement of green transformation, the new energy vehicle (NEV) industry is increasingly dependent on technological innovation. However, enterprises generally face challenges such as technological complexity, insufficient organizational capabilities, and environmental uncertainties, and there are differences in innovation performance. Most of the existing studies adopt static and linear methods, making it difficult to reveal its complex and diverse generation mechanisms. To address these limitations, this study draws on the technology-organization-environment (TOE) framework to explore the multiple pathways through which NEV firms can achieve high innovation performance. Using a sample of the NEV companies from China's A-share market between 2018 and 2022, the study employs a dynamic qualitative comparative analysis (QCA) to identify and synthesize configurational pathways. The findings reveal four effective pathways to high innovation performance, which can be categorized into two typical mechanisms: the "Incentive-responsive innovation pattern" and the "Capability-synergy innovation pattern." Further analysis shows that capability-oriented pathways exhibit greater structural stability and cross-temporal applicability, while incentive-driven pathways are more sensitive to external environmental changes. Spatially, incentive-responsive paths are more prevalent and effective in eastern regions, reflecting the differentiated impact of regional resources and policy environments. This study not only extends the application of the TOE framework but also demonstrates the methodological value of dynamic QCA in uncovering time causal configurations. The findings offer insights for NEV firms in formulating differentiated innovation strategies and for policymakers in designing region-specific support measures.

1. Introduction

In the context of the "dual carbon" strategy and the global shift toward renewable energy, the new energy vehicle (NEV) sector has quickly become a driving force for green technological innovation and sustainable development. With more automakers entering the sector and a shifting market environment, inter-firm competition is intensifying. In response to escalating market pressures and accelerating technological change, innovation has become a core capability for NEV firms to maintain their competitive advantage(Xu and Chen, 2020). Although the industry as a whole is growing rapidly, there are notable differences in innovation performance across firms. Some continuously overcome technological bottlenecks, while others become trapped in path dependence and the dilemma of capacity(Han et al., 2022; Yeung, 2019). This divergence has raised a pressing question in both academic and industry circles: How do NEV firms achieve high levels of innovation performance in a complex industrial environment?

In response to this issue, scholars have conducted extensive research on the factors influencing innovation performance, such as government incentives(S. Fu et al., 2024; Li et al., 2022), venture capital(Jiang and Liu, 2024), resource input(Xu and Chen, 2020), and technological capabilities(Ma et al., 2023; Wu et al., 2020). However, these studies focus on the impact of single-dimensional factors and rely on linear logic and mean-centric analytical methods(S. Fu et al., 2024; Ma et al., 2023; Wu, 2023). Such paradigms present certain limitations in the NEV industry, which is characterized by high complexity, dynamic uncertainty, and diverse technological trajectories. While some recent studies emphasized the importance of causal complexity, highlighting that innovation performance often emerges from the interaction of multiple conditions rather than being driven by a single linear factor(Kraus et al., 2018; Pang et al., 2025), systematic analyses of this multi-path generative mechanism remain scarce.

Against this backdrop, this study introduces the technology–organization–environment (TOE) framework to address the limitations of single-dimensional factor analyses. TOE posits that a firm's technology adoption and innovation are shaped by the interplay of technological capabilities, organizational characteristics, and external environmental factors(Baker, 2012). This framework has been widely applied in digital transformation, green innovation, and related fields, and is recognized for its robust structure and adaptability(Baker, 2012; Li et al., 2025; Reyes-Mercado and Hernandez, 2025). Unlike traditional approaches that analyze isolated variables, TOE offers a systems integration perspective, allowing for a structured examination of how different combinations of factors jointly influence innovation performance under varying conditions. It provides a good theoretical foundation for uncovering multi-path mechanisms.

However, a single theoretical framework is not sufficient to capture the multi-path phenomena present in complex contexts. Methodologically, qualitative comparative analysis (QCA) has become an important tool for identifying causal configurations and has been widely applied in organizational and innovation research in recent years(Fiss, 2011; Kraus et al., 2018). QCA emphasizes configurationality, asymmetry, and multiple conjunctural causation, offering methodological support for investigating complex phenomena(Kumar et al., 2022). However, most existing QCA studies are based on cross-sectional data, focusing on the identification of static pathways while overlooking the dynamic processes through which these paths evolve (Bhattacharya, 2023). In the context of the NEV industry, where institutional policies are frequently adjusted and technological cycles change rapidly, the innovation paths adopted by firms are often phased, adaptive, and evolutionary. As a result, static analyses struggle to capture path stability or strategic shifts. Incorporating the temporal dimension through a dynamic QCA approach can effectively address these methodological limitations and offer a more comprehensive explanation.

Building on this foundation, this study investigates the mechanisms through which innovation performance is achieved in NEV firms. Anchored in the TOE theoretical framework, it develops a structured set of conditions and applies a dynamic QCA approach to analyze representative firms in China's NEV industry between 2018 and 2022. Specifically, the study seeks to uncover: (1) the multiple configurational paths that lead to high innovation performance; (2) how these paths evolve over time; and (3) the underlying conditional logics that characterize each path. This research contributes in three key ways: (1)on the methodological front, it extends QCA from a static to a dynamic perspective, addressing the current gap in longitudinal configurational analysis. (2) At the theoretical level, it integrates the TOE framework to systematically identify how combinations of technological, organizational, and environmental factors jointly shape innovation outcomes. (3) From a practical standpoint, the findings offer actionable insights for firms to formulate differentiated innovation strategies and for policymakers to design adaptive, stage-specific policy interventions.

2. Literature review and theoretical framework

2.1. Literature review

Innovation performance is widely regarded as a key indicator for assessing a firm's innovation capability and the efficiency of transforming innovation outcomes. Fundamentally, it reflects an organization's ability to achieve effective integration among knowledge accumulation, technological development, and market application(Dewangan and Godse, 2014). Unlike traditional financial performance, innovation performance places greater emphasis on the continuity and disruptiveness of technological advancement, capturing whether a firm can secure long-term competitive advantage through innovation activities(Dewangan and Godse, 2014). Therefore, understanding the mechanisms underlying innovation performance not only aids in evaluating a firm's adaptability in complex environments but also provides a theoretical foundation for policymakers to optimize innovation support systems.

In recent years, the NEV industry has received widespread attention due to its strategic role in driving the transition toward a green and low-carbon economy. As a vital force in promoting technological breakthroughs and sustainable industrial growth, the question of how to enhance innovation performance in this sector has increasingly become a focal point of academic inquiry. In related research, scholars have primarily adopted a range of theoretical frameworks, including the resource-based view (RBV), institutional theory, and dynamic capabilities theory, to explain the innovation performance among NEV firms. The RBV emphasizes the importance of internal resources, suggesting that research and development(R&D) investment, technological capability, and human capital form the essential foundation of innovation performance(Liu et al., 2025). Institutional theory focuses on the institutional environment in which firms are embedded, especially how external institutional arrangements such as government subsidies, industrial policies, and regulatory frameworks influence firms' innovation(S. Fu et al., 2024; Kang and Choung, 2024; Shen et al., 2016). At the same time, organizational behavior theories such as dynamic capabilities and ambidextrous innovation highlight how firms respond to rapidly changing environments and foster innovation through strategic flexibility, organizational learning, and managerial competencies(Al-Shami and Rashid, 2021; Pandit et al., 2018).

However, these theoretical perspectives appear insufficient when applied to the highly systematized and interdisciplinary nature of the NEV industry. Most existing studies rely on a single perspective for variable selection, focusing on the explanatory power of one specific dimension while lacking a systematic analysis of the interrelationships among technological, organizational, and environmental factors. This form of "structural fragmentation" in theoretical construction has, to a certain extent, limited our comprehensive understanding of the mechanisms that drive innovation performance. To address this gap, this study adopts the TOE framework, which provides a systematic perspective, allowing for the integration and configuration of multiple contextual factors within a unified theoretical model(Baker, 2012; Sun et al., 2025).

2.2. The TOE theory

In the context of rapidly evolving technologies and increasingly complex and diverse markets, the effectiveness of corporate innovation activities depends not only on technological advancement itself but also on the profound influence of internal organizational characteristics and external environmental factors. To systematically understand this multidimensional interaction mechanism, the TOE framework offers a well-structured analytical perspective. This framework suggests that firms' technology adoption and innovation are influenced by technological, organizational, and environmental contexts. The technological context refers to the relevant technologies available to the firm and their compatibility; the organizational context includes internal capabilities such as resource structure, managerial competence, and firm size; and the environmental context encompasses macro-level institutional factors such as market structure, government policy, and competitive dynamics (Baker, 2012; Xing et al., 2023).

In recent years, the TOE framework has been widely applied across various research domains, including digital transformation, green technology adoption, information systems implementation, and intelligent manufacturing, demonstrating strong theoretical inclusiveness and explanatory power. For example, in green innovation, Li et al. (2025) employed the TOE framework to identify multiple pathways to green innovation in logistics enterprises. Similarly, in the intelligent and connected vehicle industry, Sun et al. (2025) utilized the framework to systematically examine the mechanisms through which policy mixes influence the industry's original innovation capacity. These studies confirm the TOE framework's applicability in addressing multi-factor interaction structures and unraveling complex causal relationships.

In the NEV industry, which integrates high technological intensity, organizational heterogeneity, and policy-driven characteristics, the applicability of the TOE framework becomes particularly evident. First, the diversity of technological pathways, such as battery-electric systems, intelligent connectivity, and hydrogen energy technologies, indicates that a single technological variable is insufficient to comprehensively explain the drivers of innovation performance(Hu et al., 2024). Second, firms in this industry exhibit significant differences in organizational form, with systematic variations in managerial capability, resource allocation, and strategic competence(Helfat and Maritan, 2024; Xu and Chen, 2020). Third, the external environment is highly dynamic, involving policy incentives and subsidy mechanisms, as well as market competition and external pressures related to carbon neutrality targets(S. Fu et al., 2024; Li et al., 2022; Wang et al., 2022).

2.3. Construction of framework

To better understand the factors driving innovation performance in the NEV industry, this study develops an antecedent model based on the TOE framework. This framework emphasizes that firms' innovation behavior results from the interaction of multiple internal and external factors, making it well-suited for explaining complex causal phenomena characterized by multiple pathways and conditions. Based on this theoretical foundation, six core variables are selected as antecedent conditions, categorized under technological, organizational, and environmental dimensions. Figure 1 presents an overview of the conceptual framework developed in this study.

2.3.1.Technical conditions

In terms of technical conditions, this study selects two variables: R&D investment and R&D capability, which represent the breadth of a firm's technological resource allocation and the depth of its technological transformation, respectively. R&D investment reflects the strategic importance a firm places on

technological innovation and serves as a critical material foundation for achieving technological breakthroughs(Athira and Nair, 2023; Wu et al., 2020; Xu et al., 2021). In the NEV industry, firms must maintain continuous investment to respond to the rapid development of core technologies such as batteries, drive systems, and in-vehicle intelligence(Hu et al., 2024; Wu et al., 2020). R&D capability reflects a firm's ability to absorb, integrate, and transform technological knowledge, encompassing various dimensions such as the competence of R&D teams, the efficiency of patent output, and the management of technological organizations(Cohen and Levinthal, 2000; Liu et al., 2023). These two variables constitute the fundamental basis for evaluating a firm's technological innovation capacity. They capture both the quantity of resources and the quality of capabilities, thereby providing dual support for the configuration of technological pathways(Cohen and Levinthal, 2000).

2.3.2.Organizational conditions

With regard to organizational conditions, this study focuses on two variables: organizational slack and managerial capability. Organizational slack refers to the pool of discretionary resources within a firm that exceeds the immediate requirements of its current operations and remains temporarily unutilized(Marlin and Geiger, 2015; Suzuki, 2018). A moderate level of slack acts as a "lubricant" for innovation, enabling flexibility and experimentation. However, excessive slack may lead to organizational inertia and inefficiency, thereby weakening the firm's innovation drive(Marlin and Geiger, 2015; Nohria and Gulati, 1997). In the NEV industry, where technological change is rapid and market uncertainty is high, organizational slack serves as a crucial condition for enhancing a firm's adaptability and capacity for trial and error. Managerial capability reflects the competence of top management in strategic integration and execution. It directly influences the efficiency of resource allocation and the realization of strategic objectives(Chen et al., 2015; Hao et al., 2024). Given the long value chain and high coordination demands of the NEV industry, managerial capability plays a critical role in mobilizing cross-departmental resources and integrating across technological platforms(Zhang et al., 2025). Therefore, the combination of organizational slack and managerial capability offers a good explanation for the internal organizational mechanisms through which firms generate innovation performance.

2.3.3.Environmental conditions

With regard to environmental conditions, this study selects market demand and government subsidies as key variables. Market demand represents the technological pull from end users or the broader industrial value chain, shaping both the market orientation and return expectations of firms' innovation efforts(Lin et al., 2013; Mowery and Rosenberg, 1979; Tang et al., 2021). Intense market demand can compel firms to accelerate technological R&D; however, it may also incentivize short-term profit-seeking behavior, potentially undermining the quality of innovation(Anning-Dorson, 2017). Government subsidies serve as a critical external driver for the development of the NEV industry, particularly in its early stages, when policy support plays a pivotal role(S. Fu et al. 2024, 2024; Li et al., 2022). Through subsidies, tax incentives, and procurement support, governments actively guide firms to increase technological investment and commit to industrial transformation(Ren and Liu, 2024). Therefore, the interaction between market demand and government subsidies constitutes a vital external condition shaping innovation performance, reflecting the combined influence of institutional and market forces(Frenkel et al., 2015).

3. Research methodology

3.1. Research method

The traditional fsQCA approach is primarily applied to cross-sectional data, emphasizing the relationship between multiple causal configurations and outcomes at a single point in time. However, this method has inherent limitations when applied to time-series data, as it cannot capture the dynamic shifts in causal mechanisms across different stages. To overcome this issue, this study adopts the dynamic QCA method proposed by Garcia-Castro and Ariño (2016), which incorporates a temporal dimension to explore the evolution of causal configurations over time.

Building on the consistency of traditional fsQCA, dynamic QCA introduces three extended consistency metrics: overall consistency reflects the general strength of causal relationships across the entire sample; inter-group consistency measures the similarity of configurations across different cases; and intra-group consistency assesses the stability of configurations within the same case over time(Bhattacharya, 2023; Garcia-Castro and Ariño, 2016). In addition, the method proposes consistency-adjusted distance metrics, such as inter-group and intra-group consistency-adjusted distance, to evaluate the stability of causal pathways across time and cases. The adjusted distance metric further controls for potential biases caused by differences in the number of configurations, thus offering a more accurate representation of how causal structures evolve over time(Bhattacharya, 2023). Given the evolutionary and stage-specific characteristics of the NEV industry, the dynamic QCA method is particularly well-suited for identifying multiple causal pathways through which firms achieve high innovation performance at different periods.

3.2. Case selection and data collection

This study examines listed companies in China's A-share market that are involved in the NEV industry. The sample is based on the *2024 Global Top 500 New Energy Companies list*, released during the Energy and Low-Carbon Development Forum on September 10, 2024. By matching this list with the NEV sector classification in the WIND database, a set of representative firms was initially identified.

To ensure data quality and analytical relevance, the following criteria were applied: (1) the company must have continuous financial and non-financial data from 2018 to 2022; (2) its main business should focus on NEV manufacturing or key components such as batteries, electric drives, or control systems, with operations of a certain scale; and (3) companies undergoing major restructuring, delisting, or with unclear business focus were excluded. A total of 36 companies met these criteria and were included in the final sample. These firms represent different segments of the industry chain and provide a reasonable level of diversity and comparability for configuration analysis.

The study focuses on six causal condition variables: R&D investment, R&D capability, organizational slack, managerial capability, market demand, and government subsidies. Data for these variables were obtained mainly from the WIND database and publicly available sources such as company annual

reports. The outcome variable, innovation performance, is measured by the number of granted patents, with data collected from the China National Intellectual Property Administration (CNIPA), the WIND database, and company disclosures. Given the time lag between innovation inputs and outputs, the causal condition variables are based on data from 2018 to 2022, while innovation performance is measured over the period 2019 to 2023. This approach helps to better identify potential causal relationships and configuration patterns.

3.3. Variable measurement

To systematically analyze the mechanisms underlying innovation performance in NEV firms, this study adopts the TOE framework. The 6 causal condition variables and one outcome variable are specified, and measurement approaches are determined based on established research to ensure both data validity and theoretical consistency. The sources and measurement criteria for all variables are summarized in Table 1.

In the technology dimension, the focus is on firms' internal innovation inputs and their capacity to absorb and apply knowledge. R&D investment is measured by annual R&D expenditure in absolute terms, reflecting the financial resources allocated to innovation activities, and indicating both the willingness and capacity to invest in innovation(Pu et al., 2022; Yu and Xu, 2022). Meanwhile, R&D capability is measured by the proportion of R&D personnel in the total workforce, capturing the firm's ability to absorb external knowledge and generate new technologies(Y. Fu et al., 2024; Volberda et al., 2010).

In the organizational dimension, the analysis emphasizes operational foundations that support innovation, particularly resource slack and managerial efficiency. Organizational slack is assessed using the ratio of period expenses to operating revenue, which reflects the level of discretionary resources available under normal operations and indicates a firm's capacity for buffering and experimentation(Depino-Besada et al., 2025; Marlin and Geiger, 2015; Singh, 1986; Suzuki, 2018). Managerial capability is measured by the total asset turnover ratio, which reflects the firm's efficiency in resource allocation and operational execution. This capability plays a critical role in the coordination and integration of resources during innovation processes(Chen et al., 2015; Hao et al., 2024).

In the environmental dimension, the study considers two external driving forces: market dynamics and policy support. Market demand is measured by revenue growth rate, which indicates market expansion trends and the intensity of customer demand. This captures the "demand-pull" effect on innovation activities(Altuzarra, 2024; Tang et al., 2021). Government subsidies are measured by the amount of government grants recognized in the firm's income statement during the period, representing the extent of policy support for firm-level innovation(Wang et al., 2022; Yu et al., 2016).

For the outcome variable, innovation performance is measured by the natural logarithm of the number of granted patents, calculated as ln(patents + 1). This indicator reflects the firm's level of technological output over a given period and has desirable statistical properties for empirical analysis(Xu et al., 2021). Considering the time lag typically associated with innovation activities, the study applies a one-year lag between the condition variables and the outcome variable—that is, values of the causal variables from a given year are used to predict innovation output in the following year. This approach improves the plausibility of causal inference(Guo et al., 2023; Xu et al., 2021).

Table 1
The measurement indicator system.

Types		Names	Measurements	Data sources
Condition Variables	Technological conditions	R&D investment	Enterprise R&D expenditure (incurred in the current period)	WIND and Annual report
		R&D capabilities	Proportion of R&D personnel to total number of employees	WIND and Annual report
	Organizational conditions	Organizational slack	Operating expense ratio	WIND and Annual report
		Management capability	The total asset turnover ratio	WIND and Annual report
	Environmental conditions	Market demand	Business revenue growth rate	WIND and Annual report
		Government subsidies	Government subsidies included in current period profit/loss	WIND and Annual report
Outcome variable		Innovation performance	Natural logarithm of (total number of granted patents + 1)	WIND, annual report, and CNIPA

3.4. Data calibration

The dynamic QCA approach requires a calibration process before analysis can be conducted (Kraus et al., 2018). Following established practices in QCA, this study applies direct calibration, using the 95th, 50th, and 5th percentiles of each variable as the anchor points for full membership, the crossover point, and full non-membership, respectively(Cangialosi, 2023; Pappas and Woodside, 2021). The calibration results and descriptive statistics are reported in Table 2.

Table 2
Calibration anchors and descriptive statistics.

Construct name		Fuzzy-set calibration			Descriptive statistics			
		Fully in	Crossover	Fully out	Minimum	Maximum	Mean	S.D.
Outcome Variable	PI	9.096	6.655	3.045	1.946	9.683	6.403	1.843
Condition Variables	R&DI	8861702087.761	744306975.900	134694104.220	53528600.370	20866192927.000	2392871367.600	3764726900.6
	R&DC	27.129	14.65	6.863	2.340	44.490	15.631	6.842
	OS	21.300	12.794	5.607	3.204	24.418	13.142	4.364
	MC	1.446	0.791	0.442	0.261	2.710	0.846	0.327
	MD	96.569	8.969	-15.331	-61.183	247.148	18.309	39.268
	GS	2078815901.711	129323828.945	15655095.603	5176211.210	4718105152.000	449641841.037	797103872.66

RDI R&D investment, *RDC* R&D capability, *OS* Organizational slack, *MC* Managerial capability, *MD* Market demand, *GS* Government subsidies, *IP* Innovation performance.

4. Results and analysis

4.1. Necessity analysis of single conditions.

Before conducting QCA analysis, it is necessary to perform a necessity analysis for each individual condition variable. A condition can be regarded as necessary for the outcome variable when its consistency level reaches 0.9(Cangialosi, 2023; Yinghui Li et al., 2024). Dynamic QCA introduces the concept of inter-group consistency-adjusted distance based on traditional QCA, to further examine the necessity of conditions(Bhattacharya, 2023; Garcia-Castro and Ariño, 2016). Specifically, when the adjusted distance exceeds the threshold of 0.2, it indicates that a more detailed analysis of necessity is needed(Garcia-Castro and Ariño, 2016).

As shown in Table 3, the overall consistency of each condition variable does not reach 0.9, but five Situations have inter-group adjusted distances greater than 0.2, suggesting the possible existence of temporal effects. A further analysis of the combinations with adjusted distances greater than 0.2 (see Table 4) shows that all inter-group consistency values are below 0.9 and coverage levels are below 0.5, indicating that a necessary relationship does not exist(Bhattacharya, 2023).

Table 3
Necessity condition analysis.

Condition variables	High-level PI				Low-level PI			
	Aggregated Consistency	Aggregated Coverage	Inter-Group Consistency Distance	Intra-Group Consistency Distance	Aggregated Consistency	Aggregated Coverage	Inter-Group Consistency Distance	Intra-Group Consistency Distance
RDI	0.849	0.793	0.025	0.301	0.604	0.531	0.066	0.493
~RDI	0.498	0.571	0.291	0.563	0.765	0.827	0.070	0.371
RDC	0.717	0.717	0.051	0.365	0.661	0.623	0.085	0.435
~RDC	0.623	0.661	0.126	0.474	0.699	0.699	0.047	0.410
OS	0.631	0.654	0.345	0.403	0.716	0.698	0.139	0.359
~OS	0.709	0.726	0.190	0.371	0.645	0.622	0.174	0.397
MC	0.697	0.692	0.073	0.435	0.687	0.642	0.028	0.384
~MC	0.640	0.684	0.149	0.467	0.671	0.676	0.076	0.365
MD	0.672	0.631	0.243	0.320	0.778	0.687	0.158	0.269
~MD	0.667	0.761	0.243	0.269	0.583	0.626	0.108	0.397
GS	0.850	0.744	0.022	0.282	0.629	0.519	0.057	0.455
~GS	0.450	0.563	0.202	0.653	0.689	0.812	0.051	0.448

The"~" symbol indicates the absence of a single variable, *RDI* R&D investment, *RDC* R&D capability, *OS* Organizational slack, *MC* Managerial capability, *MD* Market demand, *GS* Government subsidies, *IP* Innovation performance.

It is worth noting that in Situation 1, although non-R&D investment is not a necessary condition for achieving high levels of innovation performance, its necessity shows an increasing trend over time, indicating a potential temporal effect (see Fig. 2). This trend may be attributed to the fact that, as

technologies mature and market competition intensifies, relying solely on R&D investment is increasingly insufficient to meet the growing complexity of market demands and development needs(Lou et al., 2025; Qin et al., 2023; Sarpong et al., 2022). At the same time, excessive reliance on R&D investment may lead to inefficient resource allocation or even resource waste(Ng and Sánchez-Aragón, 2024; Sarpong et al., 2022).

Table 4
Inter-group data with adjusted distance greater than 0.2.

Cause-and-effect combinations		Indicators	YEAR				
			2018	2019	2020	2021	2022
Situation 1	~RDI/PI	Inter-group consistency	0.735	0.730	0.732	0.779	0.827
		Inter-group coverage	0.763	0.806	0.841	0.847	0.859
Situation 2	OS/PI	Inter-group consistency	0.667	0.618	0.683	0.804	0.774
		Inter-group coverage	0.634	0.719	0.729	0.719	0.688
Situation 3	MD/PI	Inter-group consistency	0.805	0.934	0.786	0.682	0.716
		Inter-group coverage	0.599	0.621	0.637	0.811	0.826
Situation 4	~MD/PI	Inter-group consistency	0.611	0.505	0.588	0.635	0.571
		Inter-group coverage	0.536	0.686	0.716	0.589	0.639
Situation 5	~GS/PI	Inter-group consistency	0.644	0.684	0.709	0.684	0.714
		Inter-group coverage	0.756	0.772	0.802	0.837	0.875

The"~" symbol indicates the absence of a single variable, *RDI* R&D investment, *RDC* R&D capability, *OS* Organizational slack, *MC* Managerial capability, *MD* Market demand, *GS* Government subsidies, *IP* Innovation performance.

4.2. Sufficiency analysis of the conditional configuration

Configurational sufficiency analysis is a central step in QCA, with the primary goal of examining how different combinations of conditions contribute to the outcome. In this study, dynamic panel data were analyzed using R-Studio for configurational analysis. The minimum frequency threshold for cases was set at 2, the consistency threshold for configurations at 0.8, and the PRI threshold at 0.70(Greckhamer et al., 2018). Since no condition met the criteria for necessity, no assumptions about necessary conditions were imposed.

The analysis produced enhanced parsimonious, intermediate, and complex solutions. Among these, the enhanced intermediate solution serves as the primary focus of interpretation, while the enhanced parsimonious solution is used to assist in identifying core and peripheral conditions. As presented in Table 5, four configurational pathways were identified. The overall solution consistency is 0.860, which exceeds the commonly accepted threshold of 0.70. The overall coverage is 0.753, and the overall PRI value is 0.716. Moreover, the within-configuration and between-configuration consistency-adjusted distances are both below 0.2, indicating that these four configurations represent key causal paths to achieving high innovation performance(Bhattacharya, 2023; Fiss, 2011). To improve theoretical interpretation and clarify the structure of the configurations, this study adopts a typological grouping strategy informed by underlying causal mechanisms, a common approach in fsQCA research(Fiss, 2011). Configurations that share similar logical structures and core conditions are consolidated into broader categories. As a result, two representative patterns that promote high innovation performance are identified: the "Incentive-responsive innovation pattern" and the "Capability-synergy innovation pattern." The detailed analysis is presented below.

4.2.1. Incentive-responsive innovation pattern

H1: "Incentive-responsive innovation pattern." This configuration encompasses two distinct pathways, H1a and H1b, both characterized by R&D investment as a core condition and government subsidies as a key auxiliary condition. In both pathways, firms can achieve high levels of innovation performance even in the absence of internal R&D capabilities or market demand. This finding highlights that in contexts where access to resources is not solely dependent on endogenous capabilities, the interaction between external policy incentives and firm-level investment behavior can serve as a driver of innovation(Shao and Chen, 2022).

Capchem and Longpan Technology exemplify this model. Capchem, a leading company in the field of lithium battery electrolytes for NEVs, significantly increased its R&D expenditure from 2020 to 2022, accompanied by a substantial rise in policy subsidies. This enabled the firm to maintain technological leadership in frontier areas such as high-end electrolyte additives and solid-state electrolytes. According to its annual report, Capchem's R&D spending reached RMB 530 million in 2023, more than doubling over five years, with cumulative government subsidies exceeding RMB 100 million. These funds substantially alleviated the financial pressure associated with technological breakthroughs. Notably, despite market demand volatility in 2020, the company's innovation output remained robust, and it successfully achieved mass production of several high-tech products during 2021–2022. This indicates a positive amplification effect between policy incentives and R&D investment.

Longpan Technology represents another typical pathway. Having transitioned from a traditional lubricant business to a new energy materials enterprise, the company initially lacked a strong R&D foundation. However, with strategic local government subsidies and tax incentives, it rapidly entered the lithium iron phosphate cathode material sector. By 2022, its new energy business accounted for over 85% of total revenue. Concurrently, its technology in electric drive cooling fluids gained recognition from leading domestic EV manufacturers. Although Longpan's initial R&D capabilities were relatively weak, its high

responsiveness to policy opportunities and unexpectedly strong R&D investments together formed a classic paradigm of innovation driven by the synergy of external incentives and internal input.

4.2.2. Capability synergy innovation pattern

H2: “Capability synergy innovation pattern.” This configuration includes two distinct pathways, H2a and H2b. Both are characterized by R&D investment as a core condition, with R&D capability and managerial competence acting as mutually reinforcing auxiliary conditions. In such pathways, firms in the NEV industry not only possess the capacity to allocate resources but also demonstrate the ability to effectively convert those resources into innovation outputs, thereby establishing an internally synergistic innovation mechanism. Triumph New Energy and Shanshan Corporation are representative cases of this model.

Triumph New Energy has consistently increased its R&D investment since 2018, rising from RMB 77.89 million to nearly RMB 200 million in 2022. Although its R&D capability score saw a slight decline in 2022, the company exhibited a clear upward trend in managerial performance. Data show that its management competence score increased steadily from 0.38 in 2019 to 0.51 in 2022, indicating notable achievements in organizational restructuring and process optimization. This pathway, driven by R&D input, supported by management enhancement, and oriented toward technological transformation, represents the typical logic of the H2a pattern.

Shanshan Corporation exemplifies the H2b pathway, characterized by the co-evolution of strong R&D and high-level management. Since acquiring BTR New Energy Materials, a global leader in anode materials, for over RMB 10 billion in 2020, the company has continuously advanced its technology portfolio toward international alignment. Based on its annual reports, Shanshan’s R&D investment achieved a compound annual growth rate of approximately 18.3% from 2018 to 2023. In 2022 alone, its R&D spending reached RMB 953 million, with a focus on high-barrier technologies such as artificial graphite, silicon-carbon anodes, and flexible composite current collectors. This steady growth reflects its long-term commitment to building core innovation capabilities and a focused strategy. In terms of management, Shanshan has also promoted digital transformation across its organizational and manufacturing systems. By implementing intelligent quality control systems and real-time production data platforms, the company has established a feedback mechanism among its major production bases in Ningbo, Suzhou, and Guangzhou. This significantly enhanced inter-factory knowledge sharing and organizational learning. According to data disclosed in 2022, Shanshan maintained a high management capability index of 0.73, while its R&D capability score consistently exceeded 15 points over five consecutive years. This reflects a stable and continuously improving internal capability structure. This configuration illustrates the pivotal role of endogenous capabilities in driving innovation performance and validates the wide applicability of the “capability synergy pathway” within the NEV sector.

4.3.Inter-group results

To assess the consistency and generalizability of the high-performance configurations across different periods and sample groups, this study employs inter-group consistency analysis from dynamic QCA. Specifically, we examine the inter-group consistency of the four high-performance configurations (H1a, H1b, H2a, H2b) from 2018 to 2022, drawing on Fig. 3 and Table 5. The objective is to determine whether these configurations exhibit stable structural patterns over time, thereby supporting their applicability across periods and firms, as well as their theoretical generalizability.

As shown in Fig. 3, the inter-group consistency values for all configurations exceed 0.86, well above the commonly accepted QCA threshold of 0.8(Greckhamer et al., 2018), indicating that these configurations remain sufficient conditions across different years and possess strong structural explanatory power. Among them, the H2b configuration demonstrates exceptional structural stability, maintaining consistently high consistency values over the five years (0.969 in 2018 and 0.914 in 2022), with a fluctuation range of 0.055. Although the consistency of the H2a configuration dropped to 0.880 in 2020, it generally remained within a high range (0.946–0.880) and rebounded to 0.926 in 2021, suggesting strong adaptive resilience.

As incentive-responsive configurations, the H1a and H1b paths exhibit relatively lower consistency levels compared to others; however, their values remain within an acceptable and stable range. Specifically, the consistency of H1a declined from 0.944 to 0.877, and H1b from 0.918 to 0.864, with the lowest values still exceeding 0.86. This suggests that, although externally driven configurations may be somewhat influenced by policy fluctuations(David et al., 2000), the logic underpinning their classification as high-performance configurations remains valid across periods. Furthermore, as shown in Table 5, the inter-group consistency-adjusted distances for all four configurations are well below the threshold of 0.2 (with a maximum of only 0.047), further confirming the absence of structural bias across different groups and demonstrating strong cross-group robustness(Garcia-Castro and Ariño, 2016).

In summary, the four high-performance configurations maintained a high level of consistency from 2018 to 2022, supporting the temporal stability and theoretical generalizability of the identified configurations. Notably, the H2b configuration stands out for its exceptional structural stability, indicating that the capability-synergy configuration characterized by "high R&D investment + strong management" possesses the resilience to perform across business cycles(Borah et al., 2025; Guang-lin and Tao, 2023). This makes it a key mechanism for sustaining long-term innovation performance in NEV firms. While the incentive-responsive configurations also proved effective over the five years, they exhibited greater volatility, reflecting their sensitivity to external incentive mechanisms(David et al., 2000; Liu et al., 2021). Therefore, these configurations differ in their applicability: capability-oriented configurations are better suited for fostering firms’ endogenous innovation capabilities, whereas policy-driven configurations are more appropriate during policy-stimulated stages of development.

4.4. Intra-group results

Similar to the between-group comparison, the within-group consistency-adjusted distances are all below 0.2, indicating that there are no significant differences among the four configurations across different regions(Bhattacharya, 2023; Garcia-Castro and Ariño, 2016). As shown in Table 5, the within-group consistency-adjusted distances are generally higher than the between-group distances. This suggests that the differences captured by the configurations reflect case-based variation more than temporal variation, highlighting the necessity of conducting detailed, region-specific analyses of

innovation performance among NEV firms. Based on the absence of significant within-group differences, this study further investigates the spatial distribution characteristics of each configuration. The sample of NEV enterprises is divided into two regional categories: the eastern region and the central-western region. By analyzing the differences in within-group coverage, the study examines how cases associated with different configurations are distributed across these regions. Statistical methods, including the Kruskal-Wallis rank sum test and ANOVA, are employed to test the significance of the observed distributional differences(Bhattacharya, 2023; Garcia-Castro and Ariño, 2016).

As shown in Table 6, the within-group coverage of configurations H1b and H2b did not pass the normality test (Jarque & Bera, 1980). Therefore, the Kruskal-Wallis rank sum test was applied to configurations H1b and H2b (see Table 7). In contrast, the between-group coverage of configurations H1a and H2a passed both the normality and homogeneity of variance tests, and thus were analyzed using one-way analysis of ANOVA (see Table 8). According to the results presented in Tables 7 and 8, none of the four configurations associated with high levels of innovation performance exhibit significant regional distribution differences.

Table 6
Test results of normal distribution of configuration coverage.

Configuration	Obs	Pr(Skewness)	Pr(Kurtosis)	P-value
H1a	36	-0.18	-1.24	0.04936**
H1b	36	-0.35	-0.03	0.64520
H2a	36	0.20	-1.09	0.07469*
H2b	36	0.12	-1.19	0.18360
Note. *** p < 0.01, ** p < 0.05, and * p < 0.1.				

Table 7
Results of the Kruskal-Wallis rank sum test.

Configuration	Mean	S.D.	Chi-square	P-value
H1b	0.60	0.21	1.503	0.220
H2b	0.43	0.27	0.046	0.831

Table 8
Results of the configuration one-way analysis of variance.

Configuration	Mean	S.D.	F	P-value
H1a	0.59	0.31	1.469	0.234
H2a	0.49	0.30	0.021	0.886

To further examine the average applicability of each configuration across different regions, this study presents the mean coverage values of each configuration in the eastern and central-western regions (see Table 8). The results show that the policy-driven configurations (H1a and H1b) are significantly more applicable in the eastern region than in the central-western region (Shao and Chen, 2022; Zhang and Hanaoka, 2021; Zheng et al., 2021). For instance, the average coverage of configuration H1a in the eastern region reaches 0.645, whereas it is only 0.516 in the central-western region. Provinces in the east, such as Guangdong, Jiangsu, and Zhejiang, possess strong manufacturing foundations, robust local fiscal support, and highly concentrated policy resources. Taking Guangdong as an example, in 2022, the province introduced subsidies for car purchases and the replacement of conventional fuel vehicles, with individual subsidies reaching up to 10,000 yuan. In addition, the provincial government established special funds totaling several tens of billions of yuan to promote NEVs. Guangdong also ranks among the top in the country for investment in charging infrastructure, fostering a well-developed supporting ecosystem(Ying Li et al., 2024). In contrast, while central and western regions have also been actively developing the NEV industry, their efforts are often constrained by weaker local fiscal capacities and insufficient industrial support. As a result, the overall strength of policy incentives in these regions tends to be lower(Zhang and Hanaoka, 2021). In some cases, subsidies are primarily short-term and limited in scope, offering limited sustained motivation for firms to follow policy-driven innovation paths. Consequently, configurations related to H1 tend to show lower coverage in these regions. These findings suggest that policy-driven innovation paths are more suitable for regions with strong fiscal capacities, mature policy mechanisms, and well-developed industrial ecosystems, such as those in the east. In contrast, central and western regions need to better align innovation strategies with local conditions by enhancing industrial support systems and improving fiscal investment mechanisms to increase the applicability of such paths.

Table 8
Average regional configuration coverage.

Region	Configuration			
	H1a	H1b	H2a	H2b
Eastern	0.645	0.638	0.499	0.432
Midwest	0.516	0.561	0.515	0.475

4.5. Robustness tests

To verify the robustness, the consistency threshold was first raised from 0.80 to 0.85. The results show that the configuration structure remained unchanged. Furthermore, the PRI threshold was increased from 0.70 to 0.75, revealing a clear subset relationship between the adjusted configurations and the original ones. These findings indicate that the derived configurations are highly robust and are not substantially affected by changes in parameter settings(Oana and Schneider, 2024).

5. Discussions

5.1. Main conclusions

Under the dual-carbon strategy and the broader context of green transformation, the innovation trajectories of the NEV industry have become increasingly complex and dynamic. To address the limitations of traditional studies, which rely on single-variable analysis and static causal inference. This study adopts the TOE framework(Baker, 2012) in combination with a dynamic QCA approach. Drawing on panel data from 36 publicly listed NEV firms in China between 2018 and 2022, the study identifies the generative mechanisms underpinning innovation performance and arrives at three key findings:

First, there is no single dominant pathway for innovation performance in NEV firms. Instead, multiple, equally effective causal configurations coexist. This finding echoes the concept of "causal complexity" as articulated by Fiss (2011) and Kraus et al. (2018), which posits that various combinations of conditions can lead to the same outcome depending on contextual factors. The study identifies four robust and valid configurations, which are further categorized into two archetypal innovation modes: the “Incentive-responsive innovation pattern” and the “Capability-synergy innovation pattern.”' The former emphasizes the interaction between external resource incentives (e.g., government subsidies) and firms’ strategic responses, highlighting the catalytic role of external support(Jiang and Xu, 2023; Shao and Chen, 2022). The latter centers on the internal alignment of organizational capabilities, particularly the role of R&D and managerial competence in enhancing resource conversion efficiency(Chen et al., 2015; Liu et al., 2023).

Moreover, the configuration structures demonstrate notable temporal stability and variation, reflecting firms’ dynamic adaptation to shifting innovation drivers over time. Inter-group consistency analysis based on dynamic QCA reveals that all four pathways maintained consistency scores above 0.86 during 2018–2022, indicating strong cross-period applicability(Garcia-Castro and Ariño, 2016). Among these, the capability-synergy model exhibits higher stability, suggesting that firms characterized by strong R&D and managerial capabilities are more resilient to rapid technological change and market volatility, thereby demonstrating counter-cyclical robustness(Guang-lin and Tao, 2023). By contrast, the incentive-responsive model is more sensitive to fluctuations in the external incentive environment. Although performance variability remains within an acceptable range, it does exhibit a degree of strategic uncertainty(David et al., 2000). The firms' capacity to adapt innovation strategies over time varies by type, and managers should recalibrate strategic priorities in response to both internal competencies and external conditions.

Lastly, a spatial analysis of pathway applicability reveals notable regional heterogeneity. The incentive-responsive model has a significantly higher coverage in eastern China compared to central and western regions, underscoring the influence of regional disparities in fiscal capacity, industrial foundations, and policy support systems on innovation mechanisms(Ying Li et al., 2024; Zhang and Hanaoka, 2021). For instance, provinces like Guangdong and Jiangsu benefit from stronger government subsidies, more comprehensive infrastructure, and denser innovation ecosystems, making policy-driven models more feasible and impactful. In contrast, firms in central and western regions are more reliant on internal capability building or on establishing long-term government-business partnerships to compensate for institutional shortcomings. This finding suggests that innovation policy should avoid one-size-fits-all solutions. Instead, differentiated and modular policy designs, tailored to regional development stages and industrial characteristics, are essential for fostering localized innovation.

5.2. Theoretical implications

First of all, this research extends the applicability of the TOE framework to the context of innovation in complex industries. Traditionally, the TOE model has been employed to analyze firm behaviors in areas such as technology adoption and digital transformation. By systematically applying this framework to the NEV sector, this study identifies and constructs a multi-dimensional configuration of antecedent conditions encompassing technological capabilities, organizational characteristics, and external environmental factors. The empirical findings demonstrate that the TOE framework retains strong explanatory power and adaptability in the highly uncertain and deeply integrated context of green industries. This extends its theoretical reach into the domain of sustainable innovation(Li et al., 2025; Lou et al., 2025), thereby laying a theoretical foundation for future applications in other strategic emerging industries.

Moreover, this study uncovers the diversity and dynamic evolution of innovation pathways, deepening the application of causal complexity theory in organizational research. The two archetypal pathways identified through dynamic QCA, “Incentive-responsive innovation pattern” and the “Capability-synergy innovation pattern”, validate that innovation performance does not hinge on a single determinant but rather emerges from complex, nested configurations of multiple interacting factors(Fiss, 2011; Kraus et al., 2018). More importantly, the study further explores how these pathways behave over time, finding that the capability-synergy model exhibits higher structural stability, while the incentive-responsive model is more sensitive to policy shifts. These differences reveal distinct adaptive capacities of innovation pathways under dynamic environments. This insight not only enriches the theoretical understanding of the configuration–performance relationship but also offers conceptual support for how firms dynamically adjust innovation strategies amid environmental volatility(Bhattacharya, 2023).

Finally, this study reinforces the theoretical and methodological value of dynamic QCA in organizational and industry-level research. Unlike traditional fsQCA, which focuses primarily on static configuration relationships, dynamic QCA captures the temporal evolution of causal structures, thereby enhancing explanatory power in the analysis of complex organizational behavior and policy intervention outcomes. The application of this method in the NEV industry demonstrates that dynamic QCA can not only identify multiple effective pathways but also reveal their temporal and regional variations in applicability. This provides a methodological paradigm for incorporating time sensitivity into future research on innovation management and strategic transformation.

5.3. Practical implications

By identifying multiple causal pathways through which NEV firms can achieve high levels of innovation performance, this study offers several managerial implications for both corporate practitioners and policymakers.

On the one hand, firms should move beyond the mindset of pursuing "single-factor optimization" when formulating innovation strategies and instead adopt a configuration-based approach that emphasizes the synergy of multiple conditions. Both the incentive-responsive and capability-synergy pathways can produce favorable outcomes under different combinations of conditions. Therefore, firms should dynamically align their strategic choices with their internal resource base and the characteristics of the external environment. For instance, startups or firms with relatively limited resources may prioritize obtaining policy support and combine it with R&D investment to construct a strategy based on external incentives and internal action. In contrast, firms with stronger organizational foundations and technological capabilities should focus on developing a collaborative model that emphasizes high R&D investment and strong managerial capacity to improve innovation efficiency and sustainability.

On the other hand, managers should pay closer attention to the stability of innovation pathways and build corresponding organizational support systems. The study finds that the capability-synergy pathway exhibits greater consistency over time and structural stability. This suggests that strengthening internal R&D capabilities and managerial effectiveness is a key pillar for achieving sustained innovation performance. Accordingly, firms should continuously invest in areas such as R&D team development, the improvement of technology transfer mechanisms, and the optimization of processes and organizational structures to build a more resilient innovation system.

Finally, policymakers should prioritize regional differentiation and pathway adaptability to design more precise and layered policy instruments. The study shows that the incentive-responsive pathway is more applicable in eastern regions, while the effect of policy incentives is relatively limited in central and western regions. Governments should therefore tailor their support strategies by taking into account regional fiscal capacity, industrial infrastructure, and the composition of local enterprises. On one hand, efforts should be made to strengthen the role of leading firms in the east as drivers of R&D and innovation. On the other hand, by improving supporting infrastructure and fiscal mechanisms, policymakers can help firms in central and western regions build more stable innovation capabilities, ultimately promoting coordinated development of NEV innovation capacity across regions.

5.4. Limitations and future directions

Although this study systematically examines the innovation pathway structures in the NEV industry, several limitations remain and deserve further exploration in future research.

One limitation lies in the sample selection, which focuses primarily on publicly listed companies in China’s A-share market. While these firms are representative to some extent, there are still constraints related to firm size, governance models, and positions along the industrial value chain. To improve the generalizability and external validity of the findings, future studies could incorporate a broader range of enterprises, including non-listed firms and small to medium-sized innovation actors.

Another limitation concerns the analytical approach. Although dynamic QCA offers advantages in identifying temporal patterns of causal configurations, it does not fully capture the key turning points or the underlying mechanisms that drive pathway shifts. Future research could address this gap by incorporating event history analysis or process tracing methods, which may offer deeper insights into the logic and dynamics of pathway evolution.

In addition, the variables used in this study are primarily derived from publicly available quantitative data sources. As a result, important qualitative factors such as strategic orientation, organizational culture, and managerial values have not been included, despite their potential relevance to innovation outcomes. Future research could adopt a multi-source and mixed-method approach to incorporate these softer yet influential dimensions, thereby enriching the structural understanding of innovation behavior in NEV firms.

Abbreviations

NEV	New energy vehicle
fsQCA	Fuzzy-set qualitative comparative analysis
R&D	Research and Development
ANOVA	Analysis of variance
TOE	Technology-organization-environment

Declarations

Funding

This research was supported by the High-level Talents Proiect of Youjiang Medical University For Nationalities (No.yy2024rcsk019), and Guangxi Natural Science Foundation Project (No.2025GXNSFHA069105).

Ethics declarations

Competing interests

The author declares no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

The study does not involve human participants or their data.

References

1. Al-Shami, S., Rashid, N., 2021. A holistic model of dynamic capabilities and environment management system towards eco-product innovation and sustainability in automobile firms. Journal of Business & Industrial Marketing 37, 402–416. https://doi.org/10.1108/JBIM-04-2020-0217
2. Altuzarra, A., 2024. Innovation Persistence and Firm Growth: Do They Go Hand in Hand? J Knowl Econ 15, 18590–18616. https://doi.org/10.1007/s13132-024-01809-z
3. Anning-Dorson, T., 2017. Moderation-mediation effect of market demand and organization culture on innovation and performance relationship. Marketing Intelligence & Planning 35, 222–242. https://doi.org/10.1108/MIP-04-2016-0066
4. Athira, T.R., Nair, J.J., 2023. Diabetic Retinopathy Grading From Color Fundus Images: An Autotuned Deep Learning Approach. Procedia Computer Science, International Conference on Machine Learning and Data Engineering 218, 1055–1066. https://doi.org/10.1016/j.procs.2023.01.085
5. Baker, J., 2012. The Technology–Organization–Environment Framework, in: Dwivedi, Y.K., Wade, M.R., Schneberger, S.L. (Eds.), Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1. Springer, New York, NY, pp. 231–245. https://doi.org/10.1007/978-1-4419-6108-2_12
6. Bhattacharya, P., 2023. How to build and analyze a panel data QCA model? A methodological demonstration of Garcia-Castro and Arino's panel data QCA model. Methodological Innovations 16, 265–275. https://doi.org/10.1177/20597991231179389
7. Borah, P.S., Dogbe, C.S.K., Marwa, N., 2025. Green dynamic capability and green product innovation for sustainable development: Role of green operations, green transaction, and green technology development capabilities. Corporate Social Responsibility and Environmental Management 32, 911–926. https://doi.org/10.1002/csr.2993
8. Cangialosi, N., 2023. Fuzzy-Set Qualitative Comparative Analysis (fsQCA) in Organizational Psychology: Theoretical Overview, Research Guidelines, and A Step-By-Step Tutorial Using R Software. The Spanish Journal of Psychology 26, e21. https://doi.org/10.1017/SJP.2023.21
9. Chen, Y., Podolski, E.J., Veeraraghavan, M., 2015. Does managerial ability facilitate corporate innovative success? Journal of Empirical Finance 34, 313–326. https://doi.org/10.1016/j.jempfin.2015.08.002
10. Cohen, W.M., Levinthal, D.A., 2000. Absorptive Capacity: A New Perspective- on Learning and Innovation *, in: Strategic Learning in a Knowledge Economy. Routledge.
11. David, P.A., Hall, B.H., Toole, A.A., 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Research Policy 29, 497–529. https://doi.org/10.1016/S0048-7333(99)00087-6
12. Depino-Besada, N.I., Vázquez, X.H., Sartal, A., López-Manuel, L., 2025. An integrative review and research agenda on organizational slack: addressing assumptions, conflicted theoretical proposals and conclusions. Manag Rev Q. https://doi.org/10.1007/s11301-025-00502-y
13. Dewangan, V., Godse, M., 2014. Towards a holistic enterprise innovation performance measurement system. Technovation 34, 536–545. https://doi.org/10.1016/j.technovation.2014.04.002
14. Fiss, P.C., 2011. Building Better Causal Theories: A Fuzzy Set Approach to Typologies in Organization Research. AMJ 54, 393–420. https://doi.org/10.5465/amj.2011.60263120
15. Frenkel, A., Maital, S., Leck, E., Israel, E., 2015. Demand-Driven Innovation: An Integrative Systems-Based Review of the Literature. Int. J. Innovation Technol. Management 12, 1550008. https://doi.org/10.1142/S021987701550008X
16. Fu, S., Liu, D., Huang, F., 2024. Synergistic effect of government policy and market mechanism on the innovation of new energy vehicle enterprises. Energy 295, 130998. https://doi.org/10.1016/j.energy.2024.130998
17. Fu, Y., Wu, X., Wang, Z., 2024. Internationalization rhythm and innovation performance: The effects of internationalization speed, organizational slack, and competitive intensity. International Business Review 33, 102274. https://doi.org/10.1016/j.ibusrev.2024.102274
18. Garcia-Castro, R., Ariño, M., 2016. A general approach to panel data set-theoretic research. J. Manage. Sci. Inform. Sys. 63–67. http://dx.doi.org/10.6000/2371-1647.2016.02.06
19. Greckhamer, T., Furnari, S., Fiss, P.C., Aguilera, R.V., 2018. Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. Strategic Organization 16, 482–495. https://doi.org/10.1177/1476127018786487
20. Guang-lin, X., Tao, M., 2023. How can management ability promote green technology innovation of manufacturing enterprises? Evidence from China. Front. Environ. Sci. 10. https://doi.org/10.3389/fenvs.2022.1051636
21. Guo, K., Zhang, T., Liang, Y., Zhao, J., Zhang, X., 2023. Research on the promotion path of green technology innovation of an enterprise from the perspective of technology convergence: configuration analysis using new energy vehicles as an example. Environ Dev Sustain 25, 4989–5008. https://doi.org/10.1007/s10668-022-02253-2
22. Han, J., Guo, J.-E., Cai, X., Lv, C., Lev, B., 2022. An analysis on strategy evolution of research & development in cooperative innovation network of new energy vehicle within policy transition period. Omega 112, 102686. https://doi.org/10.1016/j.omega.2022.102686
23. Hao, X., Wen, S., Zhu, J., Wu, H., Hao, Y., 2024. Can business managerial capacity improve green innovation in different industries? Evidence from Chinese listed companies. Business Strategy and the Environment 33, 2600–2620. https://doi.org/10.1002/bse.3600

24. Helfat, C.E., Maritan, C.A., 2024. Resource Allocation Capability and Routines in Multibusiness Firms. Organization Science 35, 1110–1130. https://doi.org/10.1287/orsc.2022.16778
25. Hu, R., Cai, T., Xu, W., 2024. Exploring the technology changes of new energy vehicles in China: Evolution and trends. Computers & Industrial Engineering 191, 110178. https://doi.org/10.1016/j.cie.2024.110178
26. Jiang, C., Liu, D., 2024. Effects of venture capital on green technology innovation in new energy vehicle industry in China. Energy & Environment 35, 418–437. https://doi.org/10.1177/0958305X221130135
27. Jiang, Z., Xu, C., 2023. Policy incentives, government subsidies, and technological innovation in new energy vehicle enterprises: Evidence from China. Energy Policy 177, 113527. https://doi.org/10.1016/j.enpol.2023.113527
28. Kang, D., and Choung, J.-Y., 2024. How do changing institutional logics affect innovation? The cases of Online Electric Vehicle and Fuel Cell Electric Vehicle in Korea. Industry and Innovation 31, 784–807. https://doi.org/10.1080/13662716.2023.2254265
29. Kraus, S., Ribeiro-Soriano, D., Schüssler, M., 2018. Fuzzy-set qualitative comparative analysis (fsQCA) in entrepreneurship and innovation research – the rise of a method. Int Entrep Manag J 14, 15–33. https://doi.org/10.1007/s11365-017-0461-8
30. Kumar, S., Sahoo, S., Lim, W.M., Kraus, S., Bamel, U., 2022. Fuzzy-set qualitative comparative analysis (fsQCA) in business and management research: A contemporary overview. Technological Forecasting and Social Change 178, 121599. https://doi.org/10.1016/j.techfore.2022.121599
31. Li, H., Qi, H., Cao, H., Yuan, L., 2022. Industrial Policy and Technological Innovation of New Energy Vehicle Industry in China. Energies 15, 9264. https://doi.org/10.3390/en15249264
32. Li, S., Zhu, J., Chen, P., Li, Z., Liao, C., Feng, W., 2025. Exploring high-performance green innovation in China's logistics companies: a TOE framework based on fsQCA. Front. Environ. Sci. 12. https://doi.org/10.3389/fenvs.2024.1511269
33. Li, Ying, Huang, Y., Liang, Y., Song, C., Liao, S., 2024. Economic and carbon reduction potential assessment of vehicle-to-grid development in guangdong province. Energy 302, 131742. https://doi.org/10.1016/j.energy.2024.131742
34. Li, Yinghui, You, X., Sun, X., Chen, J., 2024. Dynamic assessment and pathway optimization of agricultural modernization in China under the sustainability framework: An empirical study based on dynamic QCA analysis. Journal of Cleaner Production 479, 144072. https://doi.org/10.1016/j.jclepro.2024.144072
35. Lin, R.-J., Tan, K.-H., Geng, Y., 2013. Market demand, green product innovation, and firm performance: evidence from Vietnam motorcycle industry. Journal of Cleaner Production, Special Volume: Sustainable consumption and production for Asia: Sustainability through green design and practice 40, 101–107. https://doi.org/10.1016/j.jclepro.2012.01.001
36. Liu, J., Liu, G., Cui, H., Chen, Y., 2023. The Chinese automobile industry's research and development capability and innovative performance. Front. Psychol. 13. https://doi.org/10.3389/fpsyg.2022.1093305
37. Liu, S., Du, J., Zhang, W., Tian, X., 2021. Opening the box of subsidies: which is more effective for innovation? Eurasian Bus Rev 11, 421–449. https://doi.org/10.1007/s40821-020-00178-2
38. Liu, Y., Guo, Z., He, Q., 2025. Configuring Technological Innovation and Resource Synergies for Performance in New Energy Vehicle Enterprises: A Path Analysis Using Empirical and Comparative Methods. Sustainability 17, 5196. https://doi.org/10.3390/su17115196
39. Lou, S., Yao, C., Zhang, D., 2025. How to promote green innovation of high-pollution firms? A fuzzy-set QCA approach based on the TOE framework. Environ Dev Sustain 27, 4911–4935. https://doi.org/10.1007/s10668-023-04107-x
40. Ma, X., Jiang, H., Tong, L., Zhang, J., Dong, M., 2023. Sustainability of the New Energy Automobile Industry: Examining the Relationship among Government Subsidies, R&D Intensity, and Innovation Performance. Sustainability 15, 14794. https://doi.org/10.3390/su152014794
41. Marlin, D., Geiger, S.W., 2015. A reexamination of the organizational slack and innovation relationship. Journal of Business Research 68, 2683–2690. https://doi.org/10.1016/j.jbusres.2015.03.047
42. Mowery, D., Rosenberg, N., 1979. The influence of market demand upon innovation: a critical review of some recent empirical studies. Research Policy 8, 102–153. https://doi.org/10.1016/0048-7333(79)90019-2
43. Ng, D., Sánchez-Aragón, L., 2024. How much is enough? The role of R&D investment in the innovation process. Knowledge and Process Management 31, 309–324. https://doi.org/10.1002/kpm.1786
44. Nohria, N., Gulati, R., 1997. What is the optimum amount of organizational slack?: A study of the relationship between slack and innovation in multinational firms. European Management Journal 15, 603–611. https://doi.org/10.1016/S0263-2373(97)00044-3
45. Oana, I.-E., Schneider, C.Q., 2024. A Robustness Test Protocol for Applied QCA: Theory and R Software Application. Sociological Methods & Research 53, 57–88. https://doi.org/10.1177/00491241211036158
46. Pandit, D., Joshi, M.P., Sahay, A., Gupta, R.K., 2018. Disruptive innovation and dynamic capabilities in emerging economies: Evidence from the Indian automotive sector. Technological Forecasting and Social Change 129, 323–329. https://doi.org/10.1016/j.techfore.2017.09.035
47. Pang, Q., Zheng, H., Zhang, L., Chiu, Y., 2025. How does the regional digital innovation ecosystem lead to high energy efficiency? An exploratory study based on fsQCA. Renewable Energy 253, 123602. https://doi.org/10.1016/j.renene.2025.123602
48. Pappas, I.O., Woodside, A.G., 2021. Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. International Journal of Information Management 58, 102310. https://doi.org/10.1016/j.ijinfomgt.2021.102310
49. Pu, G., Zhu, X., Dai, J., Chen, X., 2022. Understand technological innovation investment performance: Evolution of industry-university-research cooperation for technological innovation of lithium-ion storage battery in China. Journal of Energy Storage 46, 103607. https://doi.org/10.1016/j.est.2021.103607

50. Qin, Z., Lu, Q., Yao, Z., 2023. The Impact of R&D Investment and Policy Support on Intelligent Manufacturing Level: Based on the fsQCA Method. Mathematical Problems in Engineering 2023, 4265155. https://doi.org/10.1155/2023/4265155
51. Ren, H., and Liu, Z., 2024. The impact of government subsidies on R&D investment of listed companies in China's new energy vehicle industry-based on the perspective of industrial chain. Asian Journal of Technology Innovation 32, 364–390. https://doi.org/10.1080/19761597.2023.2246046
52. Reyes-Mercado, P., Hernandez, G.J.L., 2025. Digital enablers of entrepreneurial innovation: fsQCA and NCA analysis. Journal of Organizational Effectiveness: People and Performance 12, 226–251. https://doi.org/10.1108/JOEPP-02-2024-0055
53. Sarpong, D., Boakye, D., Ofosu, G., Botchie, D., 2022. The three pointers of research and development (R&D) for growth-boosting sustainable innovation system. Technovation 122. https://doi.org/10.1016/j.technovation.2022.102581
54. Shao, Y., Chen, Z., 2022. Can government subsidies promote the green technology innovation transformation? Evidence from Chinese listed companies. Economic Analysis and Policy 74, 716–727. https://doi.org/10.1016/j.eap.2022.03.020
55. Shen, Q., Feng, K., Zhang, X., 2016. Divergent technological strategies among leading electric vehicle firms in China: Multiplicity of institutional logics and responses of firms. Science and Public Policy 43, 492–504. https://doi.org/10.1093/scipol/scv056
56. Singh, J.V., 1986. Performance, Slack, and Risk Taking in Organizational Decision Making. AMJ 29, 562–585. https://doi.org/10.5465/256224
57. Sun, D., Dong ,Kun, and Hu, S., 2025. How does policy mix promote the creational and original capacity of the intelligent connected vehicles industry? A configurational approach to the TOE framework. Technology Analysis & Strategic Management 0, 1–15. https://doi.org/10.1080/09537325.2025.2462153
58. Suzuki, O., 2018. Enabling or constraining? Unraveling the influence of organizational slack on innovation. Industrial and Corporate Change 27, 555–575. https://doi.org/10.1093/icc/dtx046
59. Tang, T. (Ya), Zhang, S. (Katee), Peng, J., 2021. The value of marketing innovation: Market-driven versus market-driving. Journal of Business Research 126, 88–98. https://doi.org/10.1016/j.jbusres.2020.12.067
60. Volberda, H.W., Foss, N.J., Lyles, M.A., 2010. PERSPECTIVE—Absorbing the Concept of Absorptive Capacity: How to Realize Its Potential in the Organization Field. Organization Science 21, 931–951. https://doi.org/10.1287/orsc.1090.0503
61. Wang, Z., Li, X., Xue, X., Liu, Y., 2022. More government subsidies, more green innovation? The evidence from Chinese new energy vehicle enterprises. Renewable Energy 197, 11–21. https://doi.org/10.1016/j.renene.2022.07.086
62. Wu, A., 2023. Collaborative eco-innovation and green knowledge acquisition: The role of specific investments in Chinese new energy vehicle industry. Business Strategy and the Environment 32, 2245–2260. https://doi.org/10.1002/bse.3246
63. Wu, Y., Gu, F., Ji, Y., Guo, J., Fan, Y., 2020. Technological capability, eco-innovation performance, and cooperative R&D strategy in new energy vehicle industry: Evidence from listed companies in China. Journal of Cleaner Production 261, 121157. https://doi.org/10.1016/j.jclepro.2020.121157
64. Xing, X., Chen, T., Yang, X., Liu, T., 2023. Digital transformation and innovation performance of China's manufacturers? A configurational approach. Technology in Society 75, 102356. https://doi.org/10.1016/j.techsoc.2023.102356
65. Xu, J., Wang ,Xiuhua, and Liu, F., 2021. Government subsidies, R&D investment and innovation performance: analysis from pharmaceutical sector in China. Technology Analysis & Strategic Management 33, 535–553. https://doi.org/10.1080/09537325.2020.1830055
66. Xu, X.L., Chen, H.H., 2020. Exploring the innovation efficiency of new energy vehicle enterprises in China. Clean Techn Environ Policy 22, 1671–1685. https://doi.org/10.1007/s10098-020-01908-w
67. Yeung, G., 2019. 'Made in China 2025': the development of a new energy vehicle industry in China. Area Development and Policy 4, 39–59. https://doi.org/10.1080/23792949.2018.1505433
68. Yu, F., Guo, Y., Le-Nguyen, K., Barnes, S.J., Zhang, W., 2016. The impact of government subsidies and enterprises' R&D investment: A panel data study from renewable energy in China. Energy Policy 89, 106–113. https://doi.org/10.1016/j.enpol.2015.11.009
69. Yu, Y., Xu, Q., 2022. Influencing Factors of Enterprise R&D Investment: Post-Subsidy, Sustainability, and Heterogeneity. Sustainability 14, 5759. https://doi.org/10.3390/su14105759
70. Zhang, R., Hanaoka, T., 2021. Deployment of electric vehicles in China to meet the carbon neutral target by 2060: Provincial disparities in energy systems, CO2 emissions, and cost effectiveness. Resources, Conservation and Recycling 170, 105622. https://doi.org/10.1016/j.resconrec.2021.105622
71. Zhang, T., Fu, Y., Hu, J., 2025. How to Improve the Efficiency of the New Energy Vehicle Industry: Multiple Paths From Configuration Perspective. Managerial and Decision Economics 46, 2643–2661. https://doi.org/10.1002/mde.4490
72. Zheng, Y., Han, W., Yang, R., 2021. Does government behaviour or enterprise investment improve regional innovation performance? - evidence from China. International Journal of Technology Management 85, 274–296. https://doi.org/10.1504/IJTM.2021.115266

Table 5

Table 5 is available in the Supplementary Files section.

Figures

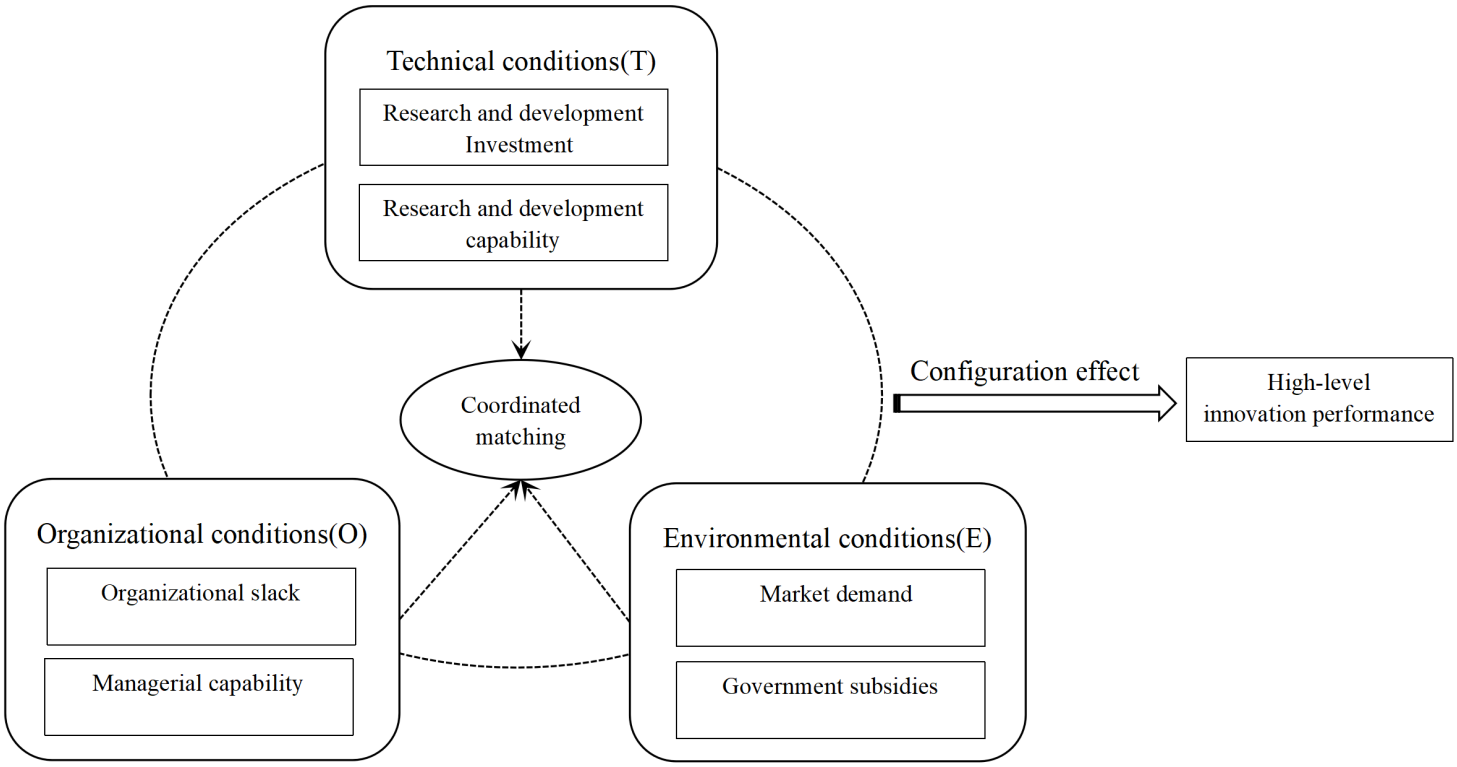

Figure 1

Conceptual model of innovation performance for the NVE industry.

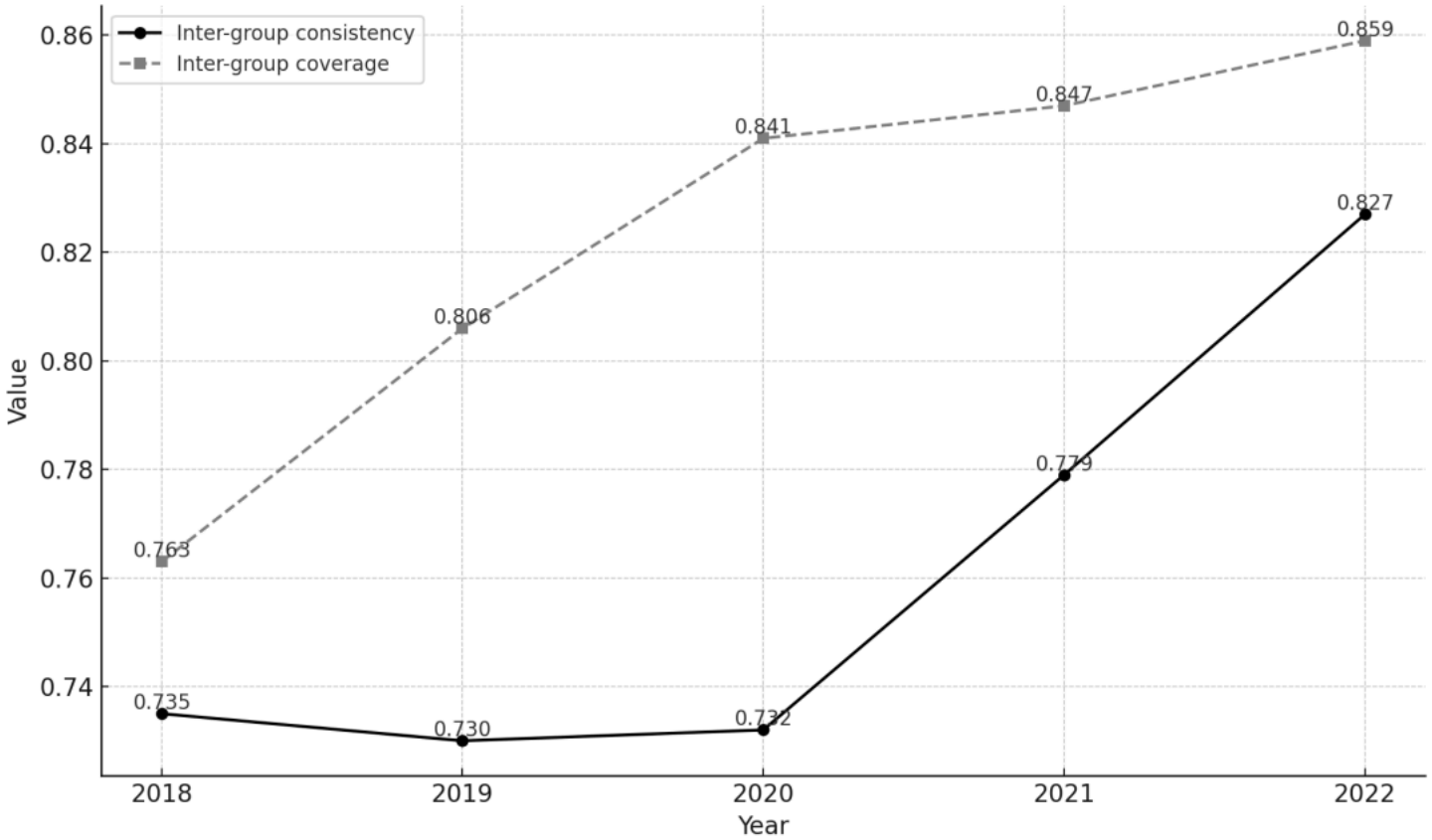

Figure 2

Trend of inter-group consistency and coverage of Situation 1.

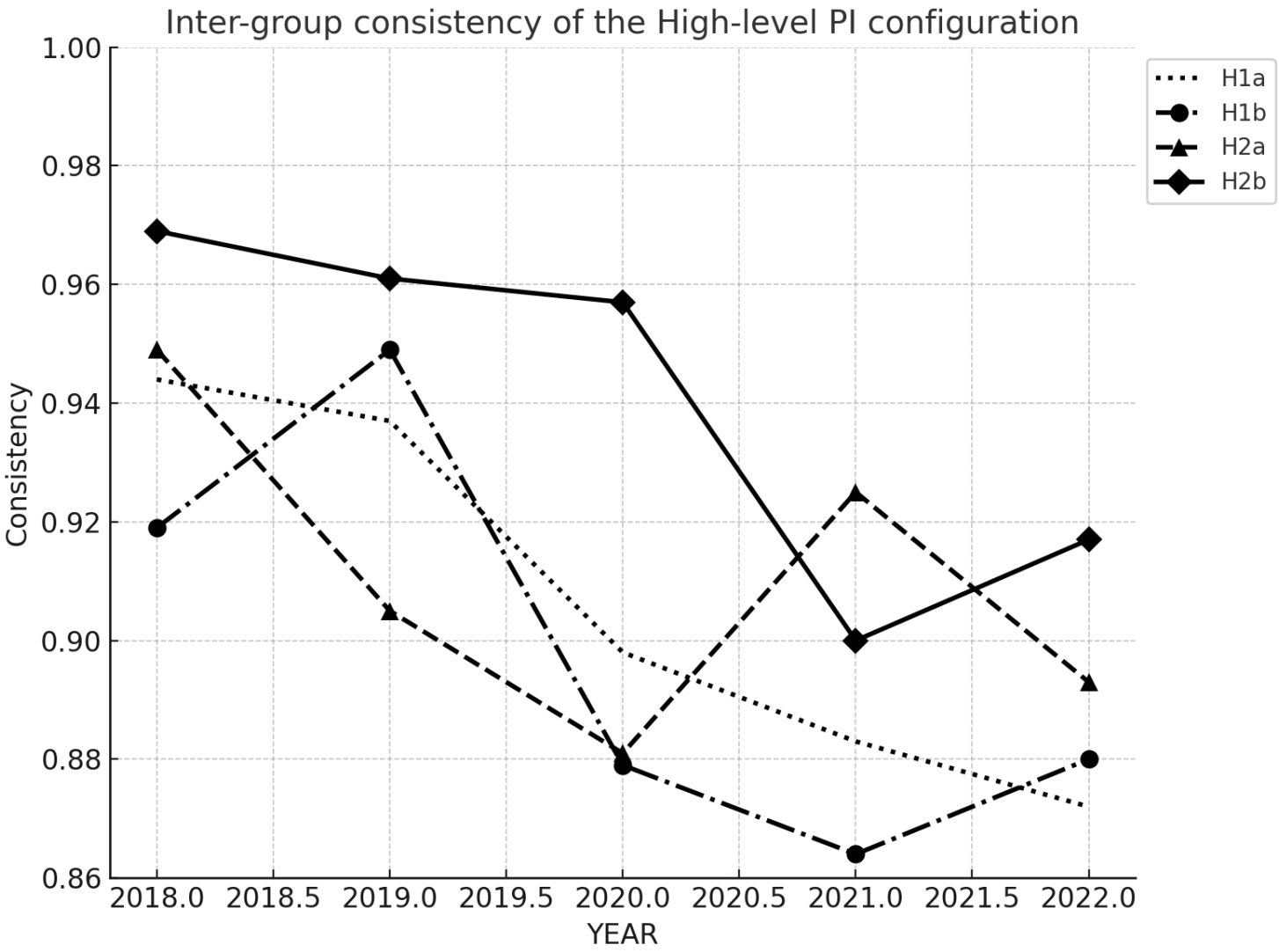

Figure 3

Variation in consistency between High-level PI configuration groups.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Table5.docx