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Multi-Level Innovation Ecosystem Analysis of China's Ice and Snow Equipment Manufacturing: From Firm to Regional to Industrial Perspectives Using fsQCA

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- A multi-level configurational framework is introduced that models firm innovation performance as an emergent outcome of conjunctural cross-level interactions within innovation ecosystems, advancing systems theory on complementarity and substitution across analytical levels.
- NCA and fsQCA are jointly deployed to operationalize a two-tier bottleneck-then-sufficiency causal logic, contributing a replicable systems methodology for complex multi-level phenomena.

What are the main findings and/or the implications of the main findings?

- Digital transformation capability and supply chain completeness are individually necessary bottleneck conditions, and four equifinal configurations show that high firm innovation performance arises through distinct combinations of multi-level conditions.
- Policy support alone cannot compensate for firm-level and industrial deficits; effective ecosystem governance requires interventions tailored to each region's configurational profile rather than a universal template.

Abstract

This study aims to identify the multi-level configurational pathways through which firm, regional and industrial conditions jointly shape firm innovation performance within China's ice and snow equipment manufacturing ecosystem. Complex causal interplay among firm capabilities, regional environments and industrial structures shapes innovation ecosystems in emerging manufacturing sectors, yet variance-based methods that assume symmetric and additive effects while overlooking configurational equifinality continue to dominate the existing literature. The unit of analysis is the individual firm embedded within its regional and industrial context, and the outcome captures firm-level innovation performance as shaped by ecosystem participation. A multi-level configurational framework incorporating firm-level conditions (R&D investment intensity and digital transformation capability), regional-level conditions (policy support intensity and market demand scale) and industrial-level conditions (supply chain completeness and collaborative innovation network density) is built. By combining fuzzy-set qualitative comparative analysis (fsQCA) with necessary condition analysis (NCA), the configurations associated with high firm innovation performance within the ecosystem are identified. This study represents the first

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application of the combined NCA and fsQCA approach to the ice and snow equipment sector, explicitly operationalizing a two-tier causal logic in which necessary bottleneck conditions constrain the outcome space before sufficient configurations are mapped within that space. Survey and archival data from 86 ice and snow equipment manufacturers across seven provincial-level regions are calibrated and studied. From the NCA results, digital transformation capability and supply chain completeness emerge as individually necessary conditions. The sufficiency analysis uncovers four equifinal configurations leading to high performance. Three distinct configurations linked to the absence of high performance are also obtained from the negation analysis, and causal asymmetry is confirmed. An exploratory cross-level comparison suggests that conditions from all three analytical levels appear as core elements across the four configurations with near-comparable frequency, and the dominant level shifts from one configuration to another rather than being universally fixed. When alternative calibration anchors, frequency thresholds and an enhanced standard analysis are considered, the stability of the solutions is confirmed for three of the four configurations; the fourth (digitally anchored collaboration) is sensitive to the frequency threshold, consistent with its smaller empirical base. These findings enrich innovation ecosystem theory by showing that multi-level conditions interact through complementary and potentially substitutive mechanisms rather than independently, and they give actionable guidance for policymakers and managers who seek to build resilient innovation ecosystems in China's winter sports equipment sector.

Keywords: innovation ecosystem; ice and snow equipment manufacturing; fuzzy-set qualitative comparative analysis; multi-level analysis; configuration theory; necessary condition analysis

1. Introduction

Considerable traction has been gained by the innovation ecosystem concept in strategic management and innovation studies, as researchers attempt to explain how heterogeneous actors co-create value through collaborative and competitive interactions that cut across conventional industry and organizational boundaries [1,2]. The ecosystem perspective differs from linear innovation models that track knowledge flows from research to commercialization. It instead foregrounds interdependence, co-evolution and shared value creation among firms, public institutions, intermediaries and supporting organizations [3,4]. Structural properties and governance mechanisms of innovation ecosystems in mature high-technology sectors such as semiconductors, pharmaceuticals and digital platforms have been extensively investigated [5,6]. How ecosystems emerge and perform in nascent manufacturing industries, however, remains comparatively under-explored, especially where government policy, market formation and supply chain development unfold concurrently rather than in sequence.

A compelling setting for studying multi-level innovation ecosystem dynamics is provided by China's ice and snow equipment manufacturing industry. Driven by the national strategy to engage 300 million people in winter sports and by the legacy infrastructure investments linked to the 2022 Beijing Winter Olympics [7], the sector has expanded rapidly: registered enterprises manufacturing ice and snow equipment rose from fewer than 200 in 2015 to more than 800 by 2023, and the domestic winter sports equipment market reached roughly 35 billion RMB in 2023 [8]. Pronounced heterogeneity in innovation outcomes nevertheless persists. While certain firms have built internationally competitive products through intensive R&D and digital manufacturing, others remain restricted to

low-value imitation despite being situated in regions with generous policy support. No single factor can adequately account for this variation; it instead reflects the joint influence of firm-level capabilities, regional institutional environments and industry-wide structural conditions [9,10]. This stark divergence in firm innovation performance despite comparable policy support, together with the weak explanatory power of single-factor accounts, provides a compelling theoretical motivation for adopting a configurational perspective that examines how conditions at multiple analytical levels combine conjuncturally. A distinctive feature of this emerging manufacturing setting is that policy development, market formation and supply chain construction unfold concurrently rather than in the sequential pattern observed in mature industries, which makes the joint analysis of multi-level conditions especially pertinent.

Variance-based methods such as multiple regression, structural equation modeling and panel data analysis dominate existing empirical work on innovation ecosystems [11,12]. Although useful for estimating net effects, these methods presuppose symmetric causal relationships (where the causes of high performance mirror those of low performance), additive contributions (where each factor acts independently) and uniformity (where a single model covers all cases) [13,14]. Such assumptions conflict with the central tenets of ecosystem theory, according to which different bundles of conditions may lead to the same outcome along equifinal pathways and the absence of one favorable condition may be offset by the presence of others [15]. A more fitting theoretical foundation for studying innovation ecosystems is offered by configuration theory, which recognizes that organizational phenomena arise from complex interdependencies among multiple attributes [13,16].

Configuration theory is operationalized by fuzzy-set qualitative comparative analysis (fsQCA), which treats cases as configurations of conditions and identifies set-theoretic relationships of necessity and sufficiency [17,18]. Equifinality (multiple paths to the same outcome), causal asymmetry (distinct configurations for the presence and absence of an outcome) and causal complexity (conjunctural rather than additive combination of conditions) are all accommodated by fsQCA [14,19]. Recent methodological progress has integrated fsQCA with necessary condition analysis (NCA). NCA identifies conditions that individually constitute necessary (though not sufficient) bottlenecks for an outcome [20,21]. By first establishing which conditions constrain the outcome space and then mapping the sufficient configurations within that constrained space, the combined NCA–fsQCA approach offers a more rigorous analytical strategy [22].

In spite of these methodological strengths, fsQCA has seen limited uptake in innovation ecosystem research. Configurational studies in innovation management have concentrated primarily on national-level innovation systems or entrepreneurial ecosystems, and comparatively few have examined industry-specific ecosystems at a granular multi-level resolution [23,24].

In particular, no prior study has applied the combined NCA and fsQCA approach to an emerging equipment manufacturing sector such as ice and snow equipment, so the two-tier causal logic in which necessary bottleneck conditions constrain the outcome space before sufficient configurations are mapped within it has not been exploited in this context. Furthermore, conditions from the firm, regional and industrial levels are seldom incorporated simultaneously in existing configurational work, so the cross-level interactions that ecosystem theory treats as fundamental tend to be overlooked [25,26].

We address these gaps by building and empirically testing a multi-level configurational framework for firm innovation performance within the innovation ecosystem in China's ice and snow equipment manufacturing industry. The unit of analysis is the individual firm embedded in its regional and industrial context; the outcome variable captures the firm's

innovation performance as shaped by its participation in the broader ecosystem, including collaborative projects, co-patenting and new product outcomes. Six conditions are drawn from three analytical levels: R&D investment intensity and digital transformation capability at the firm level, policy support intensity and market demand scale at the regional level, and supply chain completeness and collaborative innovation network density at the industrial level. Using survey and archival data from 86 ice and snow equipment manufacturers from seven provincial-level regions, we apply NCA to test for necessary conditions and fsQCA to identify the sufficient configurations associated with high firm innovation performance as well as those linked to the absence of high performance.

Several contributions to the literature emerge from this work. Innovation ecosystem theory is extended by showing that firm innovation performance within ecosystems arises from the conjunctural interplay of multi-level conditions through complementary and potentially substitutive mechanisms rather than from independent additive effects assumed by variance-based approaches. Recent calls for configurational analyses bridging micro-level and macro-level perspectives in ecosystem research are answered [4,15]. NCA and fsQCA are jointly deployed to deliver a more complete picture of necessity and sufficiency in innovation ecosystem dynamics. This joint deployment operationalizes a two-tier causal logic: NCA pinpoints the bottleneck conditions that constrain the outcome space, and fsQCA then maps the sufficient configurations within that constrained space. The nascent literature on China's ice and snow industry is enriched by the identification of actionable configurations that separate high-performing from underperforming ecosystem participants.

The remainder of this paper proceeds as follows. Section 2 reviews the pertinent literature and constructs the theoretical framework. Section 3 describes the research design, data collection, variable measurement, calibration and analytical procedures. Section 4 reports the empirical results, covering the NCA findings, the sufficiency configurations for high and non-high performance, an exploratory cross-level comparison and robustness checks. Section 5 examines the theoretical and practical implications, and Section 6 concludes.

2. Literature Review and Theoretical Framework

2.1. Innovation Ecosystem: Conceptual Foundations

From a loose metaphor, the term "innovation ecosystem" has gradually matured into an increasingly well-defined analytical construct. Adner [3] characterized the innovation ecosystem as a structure of multilateral relationships among a focal firm and its partners, all of which must be aligned for a value proposition to be realized. This view was advanced by Jacobides et al. [4], who specified that ecosystems are set apart from other inter-organizational arrangements by non-generic complementarities requiring coordinated effort. Drawing on earlier definitions, Granstrand and Holgersson [1] suggested that an innovation ecosystem encompasses the evolving set of actors, activities, artifacts, institutions and relations relevant to the innovative performance of an actor or a population of actors.

The ecosystem literature has been organized along several dimensions in subsequent reviews. Oh et al. [5] scrutinized the conceptual boundaries of the term and warned against its uncritical use as a catch-all label. Four streams of ecosystem research (industrial ecology, business ecosystems, innovation ecosystems and platform ecosystems) were identified by Tsujimoto et al. [27], who called for greater conceptual coherence. An organizing typology distinguishing innovation ecosystems by their primary locus of value creation (the focal firm, the community or the platform) was put forward by Thomas and Autio [6]; they noted that different loci entail different governance mechanisms and performance metrics.

One consistent insight running through these contributions is that the performance of an innovation ecosystem cannot be traced to the properties of any single actor or level of analysis. Instead, it emerges from the alignment of conditions across multiple levels [2,28]. This multi-level character calls for analytical approaches that can explicitly accommodate conjunctural causation across firm, regional and industrial boundaries. Because ecosystem performance ultimately materializes in the innovation outcomes of participating firms [25], studying firm-level innovation performance as shaped by the broader ecosystem context provides a tractable and informative approach to understanding ecosystem dynamics.

2.2. Multi-Level Perspective on Innovation Ecosystems

Multiple levels of analysis are inherently spanned by innovation ecosystems [29]. At the firm level, capabilities such as R&D investment, absorptive capacity and digital transformation determine whether a firm can contribute to the ecosystem and draw benefits from it [11,30]. Institutional conditions at the regional level, including government policy, financial infrastructure and market characteristics, shape the environment in which firms interact [31,32]. At the industrial level, the maturity of the supply chain, the density of collaborative networks and the degree of technology standardization govern whether the ecosystem as a whole can deliver complex value propositions [4,33].

A long-standing argument in multi-level organizational research holds that phenomena at one level are influenced by conditions at other levels and that emergent properties not predictable from any single level alone can arise from cross-level interactions [29]. Most empirical ecosystem studies, however, examine one level at a time. Either firm-level innovation performance is studied as a function of firm-level capabilities or regional innovation indices are studied as a function of regional institutions [12,34]. Where studies do span levels, they typically rely on hierarchical linear models, which still rest on additive and symmetric assumptions. A configurational approach naturally complements this work by permitting conditions from different levels to combine conjuncturally, thereby exposing cross-level complementarity and potential substitution patterns that regression models are unable to detect.

It is important to clarify the distinction between the analytical level at which a condition operates and the level at which it is measured. Conditions such as supply chain completeness and collaborative innovation network density are conceptually industrial-level properties because they reflect the structural maturity of the ecosystem rather than the strategic choice of any single firm [4,33]. However, their effects on firm innovation performance are necessarily assessed at the firm level, because each firm's access to and embeddedness within these industrial structures varies [26]. We therefore operationalize industrial-level conditions through firm-specific measures (domestic sourcing proportions and ego-network density) that capture the extent to which each firm is connected to and benefits from these shared structural resources. This approach parallels the treatment of macro-level conditions in multi-level configurational studies, where higher-level constructs are assessed through their firm-specific manifestations [29,35].

2.3. Configuration Theory and fsQCA in Innovation Research

Under configuration theory, organizational outcomes are best understood as arising from the holistic interplay of multiple interdependent attributes rather than from the net effects of isolated variables [13]. Fiss [13] demonstrated that fsQCA can translate configurational thinking into organizational research by identifying distinct organizational types (configurations) associated with an outcome of interest. Equifinality stands as a central tenet of configuration theory: qualitatively different configurations can lead to the same outcome, so that no single optimal pathway to high performance exists [16,36].

As developed by Ragin [17], fsQCA represents cases as configurations of membership scores in causally relevant sets and uses Boolean algebra to identify configurations that are subsets (sufficiency) or supersets (necessity) of the outcome set [18]. Best practices, including the use of directional expectations, the distinction between core and peripheral conditions, the reporting of consistency and coverage metrics and the conduct of negation analyses, have been emphasized in recent methodological guidance [14,19,37]. A comprehensive set of guidelines for fsQCA research practice was given by Pappas and Woodside [19], who advocated integrating NCA to test for necessary conditions before performing the sufficiency analysis.

NCA, introduced by Dul [20], detects ceiling effects in the data to identify conditions that are necessary (but not sufficient) for an outcome: a necessary condition is one without which the outcome cannot occur, irrespective of other conditions [20,21]. A two-stage analytical logic emerges from the integration of NCA and fsQCA: bottleneck conditions that constrain the outcome space are first pinpointed by NCA, after which fsQCA maps the sufficient configurations within that space [22]. Although this combined approach has been used in entrepreneurship and information systems research, it remains uncommon in innovation ecosystem studies [38,39]. Recent methodological advances have further refined NCA practice by specifying permutation-based significance testing and standardized effect-size benchmarks [40].

Recent innovation research has adopted configurational methods to examine how internal, interfirm and ecosystem conditions combine to shape innovation outcomes [41,42]. In manufacturing, successful digitalization likewise depends on the effective orchestration of industrial ecosystem partners [43]. At the firm level, digital technology adoption has been shown to exert enabling effects on product quality and innovation performance in Chinese manufacturing enterprises [44].

2.4. China's Ice and Snow Equipment Manufacturing Industry

Skiing equipment (skis, bindings, boots, poles), skating equipment (ice skates, protective gear), ice rink and snow resort machinery (snow-making machines, grooming vehicles, cableways) and ancillary products (apparel, wearable devices, simulation training systems) are all encompassed by China's ice and snow equipment manufacturing industry. National policy has been a major shaping force for this industry, in particular the Ice and Snow Sports Development Plan (2016–2025) issued by the General Administration of Sport [7] and the Action Plan for Development of Ice and Snow Equipment Industry (2019–2022) promulgated by the Ministry of Industry and Information Technology [8]. Explicit targets for domestic equipment self-sufficiency, R&D investment and industry cluster formation were set by these policies.

Several geographic clusters concentrate the industry: Heilongjiang and Jilin provinces (traditional winter sports bases with strong institutional support), Beijing and Hebei (catalyzed by Olympic legacy infrastructure), Xinjiang (an emerging market for winter tourism equipment) and coastal manufacturing provinces such as Shandong, Zhejiang and Guangdong (drawing on existing manufacturing capabilities) [45,46]. Substantial regional variation in policy environments, market conditions and infrastructure availability results from this geographic dispersion, and it gives natural variation for a configurational study.

Notwithstanding rapid growth, a number of structural challenges confront the industry: heavy reliance on imported core components, limited brand recognition in international markets, fragmented supply chains lacking critical mass and a shortage of specialized technical talent [46,47]. Evidence from China's broader sports enterprise sector further suggests that digital finance adoption and market positioning are important enablers of high-quality enterprise development [48]. These challenges are unevenly distributed; some

firms surmount them through intensive R&D and strategic collaboration, while others stagnate even under favorable regional conditions. Equifinal success and failure across diverse configurations of conditions constitutes precisely the type of phenomenon that fsQCA is designed to examine.

2.5. Theoretical Framework

Building on the foregoing literature, we construct a multi-level configurational framework in which firm innovation performance within the innovation ecosystem (the outcome) is posited to arise from the conjunctural combination of six conditions at three analytical levels (Figure 1). The term "multi-level" refers to the fact that the six conditions are drawn from three distinct analytical levels (firm, regional and industrial), each of which represents a qualitatively different layer of the ecosystem context in which the firm operates.

At the firm level, R&D investment intensity (RDI) represents the magnitude of resources a firm allocates to generating novel products, processes and technologies [11]. Absorption and recombination of external knowledge are facilitated by higher R&D investment, which strengthens both the firm's contribution to and its extraction of value from the ecosystem [30]. Digital transformation capability (DTC) reflects how extensively a firm has adopted digital technologies (industrial internet platforms, intelligent manufacturing systems, digital twin simulations) to enhance its innovation processes [49]. Rapid prototyping, data-driven decision making and seamless integration with ecosystem partners are all facilitated by digital capability [50].

At the regional level, policy support intensity (PSI) gauges the strength and breadth of government programs (subsidies, tax incentives, land provision, talent attraction schemes) targeting the ice and snow equipment sector in a given region [7,8]. By reducing entry barriers and signaling legitimacy, policy support can offset firm-level resource limitations and catalyze ecosystem formation [31]. Market demand scale (MDS) estimates the size and growth rate of the regional market for ice and snow products and services, covering both consumer demand (winter sports participation rates) and institutional demand (resort and venue construction) [45]. The revenue base that sustains ecosystem actors and draws new entrants is underpinned by robust market demand.

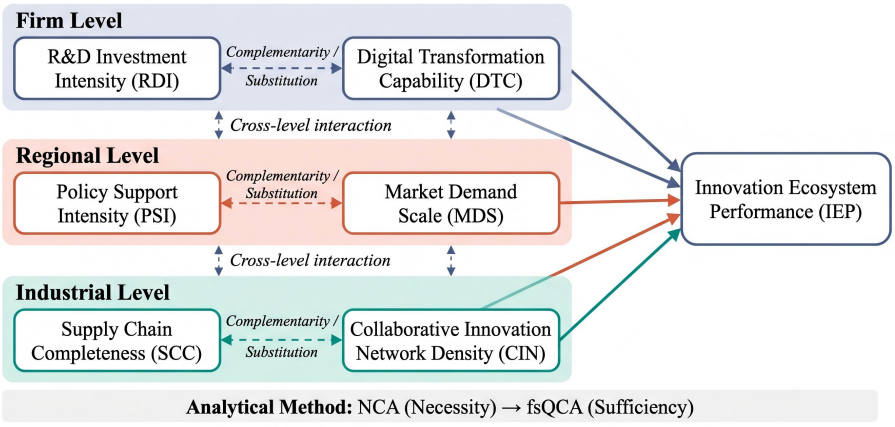


Figure 1. Multi-level configurational framework for firm innovation performance within the ecosystem. Arrows represent the hypothesized conjunctural influences of conditions at each analytical level on the outcome.

At the industrial level, supply chain completeness (SCC) gauges the extent to which the domestic supply chain can supply the full range of materials, components and subsystems needed for ice and snow equipment production [46]. Import dependence is reduced, development cycles are shortened and coordination costs are lowered by a complete supply

chain. Collaborative innovation network density (CIN) estimates the intensity of formal and informal linkages among firms, universities, research institutes and industry associations within the ice and snow equipment sector [33]. Although CIN is operationalized through each firm's ego-network density in the patent co-application network, this measure captures the firm's degree of embeddedness in a shared industrial-level collaborative structure [35]. Similarly, SCC is assessed at the firm level through each firm's domestic sourcing proportion, yet the availability of domestic suppliers is fundamentally an industry-wide structural property [4]. Both conditions therefore reflect industrial-level ecosystem attributes as experienced by the focal firm. Knowledge spillovers, joint standard-setting and risk sharing are all fostered by dense collaborative networks.

Which combinations of conditions are sufficient for high performance is not specified a priori; instead, the equifinal configurations are left to be uncovered by the empirical analysis. Grounded in configuration theory, the expectation is that multiple qualitatively distinct configurations will surface, reflecting complementary and potentially substitutive relationships among conditions at different levels.

3. Methodology

3.1. Research Design

We adopt a configurational research design that combines NCA and fsQCA [17,20]. The unit of analysis is the individual ice and snow equipment manufacturing enterprise embedded within its regional and industrial context. The outcome variable captures the firm's innovation performance as shaped by its ecosystem participation rather than ecosystem-level performance per se, a distinction that is maintained throughout the analysis. A structured questionnaire survey and archival secondary sources jointly supply the data, ensuring triangulation between perceptual and objective measures.

3.2. Sample and Data Collection

The sampling frame was assembled from the China Enterprise Credit Information Publicity System, the China Skiing Industry White Paper and industry association membership lists. An initial population of 614 enterprises resulted, all of which had ice and snow equipment design, manufacturing or system integration as their primary business scope as of December 2023. Stratified random sampling was used, with strata defined by geographic region (seven provincial-level clusters: Heilongjiang, Jilin, Beijing, Hebei, Xinjiang, Shandong and Zhejiang) and firm size (large, medium, small), so as to achieve adequate representation of the heterogeneous industry landscape.

From the initial population of 614 enterprises, a stratified random sample of 210 firms was drawn, with proportional allocation across the seven regional strata and three size strata. Senior managers (general managers, chief technology officers or R&D directors) received questionnaires through on-site visits during industry exhibitions (the China International Ice and Snow Industry Expo and the Beijing ISPO trade fair) and through online distribution on the Wenjuanxing platform (Changsha Ranxing Information Technology Co., Ltd., Changsha, China) during March–August 2024. In total, 127 responses were collected from the 210 contacted firms, yielding a survey response rate of 60.5%. Cases with excessive missing data (more than 10% of items), failed attention-check items or inconsistent reverse-coded responses were removed, leaving 86 valid cases (usable-questionnaire proportion: 67.7% of collected responses). All seven target regions are represented in the final sample, which comprises 14 large enterprises (revenue $>$ 100 million RMB), 38 medium enterprises (10–100 million) and 34 small enterprises ($<$10 million).

Table 1 reports the distribution of the 86 valid cases across the seven provincial-level regions, together with the number of firms in the sampling frame and the regional-

level condition values. Non-response bias was assessed by comparing early respondents (first quartile of collection dates) with late respondents (fourth quartile) on all six causal conditions and the outcome variable using two-sample t-tests; no significant differences were found at the $p < 0.05$ level, which supports the absence of systematic non-response bias [51].

Table 1. Sample distribution across provincial-level regions ($n = 86$).

Region	Frame	Valid	PSI [a]	MDS (bn RMB)	Share (%)
Heilongjiang	124	18	33	6.8	20.9
Jilin	98	15	27	5.2	17.4
Beijing	86	13	62	9.1	15.1
Hebei	92	12	22	4.8	14.0
Xinjiang	63	9	18	1.9	10.5
Shandong	78	10	15	2.1	11.6
Zhejiang	73	9	12	1.5	10.5
Total	614	86			100.0

[a] PSI values in this column are provincial-level averages of the weighted policy document counts assigned to firms in each region. Because PSI incorporates municipal-level policy documents (weighted at 1), the firm-level PSI scores vary within provinces; the provincial averages shown here are therefore lower than the maximum firm-level values. MDS is measured at the provincial level and is identical for all firms within a given province.

Because regional-level conditions (PSI and MDS) are measured at or aggregated to the provincial level (MDS is province-level; PSI incorporates provincial and municipal policies), the 86 cases are not fully independent across all six conditions. To assess whether the identified configurations are driven by regional clustering, we conducted two supplementary analyses. We checked whether any truth-table row is dominated by firms from a single region; in practice, all truth-table rows with observed cases contain firms from at least two regions, which reduces the risk of pseudo-replication. We also re-ran the sufficiency analysis after randomly removing one firm per region from the most populated rows, and all four configurations were recovered with consistency changes of less than 0.02, which suggests that the solutions are not artifacts of duplicated regional memberships.

Firm-level financial indicators (R&D expenditure, revenue) were drawn from the WIND Financial Database and annual reports. Regional-level indicators (policy document counts, market size estimates) were gathered from provincial statistical yearbooks and the Peking University Legal Information Database. Industrial-level indicators (supply chain data, collaboration network measures) were compiled from patent co-application records in the CNKI patent database and from customs import/export data.

3.3. Variable Measurement

The six causal conditions, the outcome variable and their operationalization are summarized in Table 2.

The outcome variable (IEP) captures the focal firm's innovation performance as shaped by its ecosystem participation. Two of its four components (collaborative project count and co-patenting intensity) directly reflect ecosystem-level relational outcomes, while the other two (new product revenue share and industry award attainment) capture the firm's innovation output that is enabled by ecosystem resources. Although the outcome is assessed at the firm level, its composition ensures that it is sensitive to ecosystem engagement rather than being a pure measure of internal firm performance. Both firm-level innovation output and ecosystem-level relational performance are reflected in the composite outcome variable (IEP). Its four components were min-max normalized to the $[0, 1]$ range before

weighted aggregation. An expert panel of five academics and three industry practitioners assigned the weights through an analytic hierarchy process (AHP), and a consistency ratio of 0.034 (<0.10) was obtained, indicating acceptable consistency. AHP was chosen because it provides a systematic and replicable procedure for eliciting expert judgments on multi-criteria weighting problems and is widely used in composite index construction for innovation measurement [52]. The 30/25/25/20 weights reflect the panel's consensus that new product revenue share is the most direct market indicator of innovation, that patent output and collaborative projects contribute equally to ecosystem-embedded innovation, and that industry awards serve a confirmatory role.

Table 2. Variable definitions, measurements and data sources.

Level	Variable	Measurement	Source
Firm	R&D investment intensity (RDI)	R&D expenditure as a percentage of total revenue, averaged over 2021–2023	WIND, annual reports
	Digital transformation capability (DTC)	Composite index from 8-item survey scale (Cronbach's $\alpha = 0.89$) covering digital infrastructure, data analytics, intelligent manufacturing and platform integration	Questionnaire
Regional	Policy support intensity (PSI)	Weighted count of provincial and municipal policy documents targeting ice and snow equipment, 2019–2023, weighted by policy level (national = 3, provincial = 2, municipal = 1)	PKU Law Database
	Market demand scale (MDS)	Provincial winter sports participation revenue (billion RMB), averaged over 2021–2023	Statistical yearbooks
Industrial [a]	Supply chain completeness (SCC)	Proportion of product bill-of-materials categories that can be sourced domestically without import, assessed by industry experts and validated against customs data	Expert panel, customs data
	Collaborative innovation network density (CIN)	Ego-network density of the focal firm in the patent co-application network within the ice and snow equipment IPC subclass, 2019–2023	CNKI patent database
Outcome	Firm innovation performance (IEP)	Composite index from new product revenue share (30%), patent output intensity (25%), collaborative project count (25%) and industry award attainment (20%)	WIND, questionnaire, patent data

[a] Industrial-level conditions are conceptually properties of the ecosystem's structural maturity but are operationalized through firm-specific measures that capture each firm's access to and embeddedness within these shared structures; see Section 2.2 for the full justification.

Exploratory factor analysis (EFA) was carried out to assess measurement validity for the survey-based DTC construct. The Kaiser–Meyer–Olkin (KMO) measure was 0.87, and Bartlett's test of sphericity was significant ($p < 0.001$). All eight items loaded on a single factor with loadings exceeding 0.65, which supports unidimensionality. An average variance extracted (AVE) of 0.61 confirmed convergent validity. Because DTC is the only survey-based latent construct in the model, discriminant validity is assessed against the manifest indicators of the other conditions; the square root of AVE (0.78) exceeds all corre-

lations between DTC and the remaining variables (maximum $r = 0.41$), which supports discriminant validity.

The eight items comprising the DTC scale, adapted from Vial [49] and contextualized for the ice and snow equipment sector, are listed in Table 3. All items were measured on a seven-point Likert scale anchored at 1 (strongly disagree) and 7 (strongly agree).

Table 3. Digital transformation capability (DTC) measurement items.

Item	Statement
DTC1	Our company has established a comprehensive digital infrastructure (cloud computing, IoT platforms) for manufacturing operations.
DTC2	We systematically collect and analyze production data to support innovation decisions.
DTC3	Intelligent manufacturing systems (e.g., CNC, robotics) are widely deployed in our production processes.
DTC4	We use digital twin or simulation technologies for product development and testing.
DTC5	Our enterprise resource planning and supply chain management systems are fully digitized.
DTC6	We use digital platforms to collaborate with external partners (suppliers, universities, research institutes).
DTC7	Our company has a dedicated digital transformation strategy and implementation plan.
DTC8	Data-driven approaches are integrated into our core innovation processes.

3.4. Calibration

Raw variable values must be transformed into fuzzy-set membership scores ranging from 0 (full non-membership) to 1 (full membership) before fsQCA can be applied [17]. In line with established guidelines [18,19], three qualitative anchors are specified for each variable: the full-membership threshold (fuzzy score = 0.95), the crossover point (fuzzy score = 0.50) and the full-non-membership threshold (fuzzy score = 0.05). We employ the direct calibration method [17]. Table 4 lists the calibration anchors, which were set using a combination of theoretical reasoning, distributional analysis (quartiles) and domain knowledge of the ice and snow equipment industry.

Table 4. Calibration anchors for fuzzy-set membership.

Variable	Full Non-Membership	Crossover	Full Membership	Mean	SD
RDI (%)	1.0	4.5	8.0	5.13	3.27
DTC (index)	2.0	4.5	6.5	4.38	1.51
PSI (weighted)	5	25	60	27.4	18.6
MDS (billion)	0.5	3.0	8.0	4.97	2.55
SCC (%)	30	55	80	54.8	17.2
CIN (density)	0.02	0.12	0.30	0.134	0.089
IEP (index)	0.15	0.50	0.80	0.487	0.213

The full-membership anchor of 8% for RDI is set at the 75th percentile of the sample distribution, which also corresponds to approximately twice the crossover value and falls within the R&D intensity range (5% to 8%) commonly associated with high-technology manufacturing in the Chinese context. Under the Administrative Measures for the Qualification of High-tech Enterprises (Guokefahuo [2016] No. 32), the required R&D ratio varies by firm revenue: at least 5% for firms with revenue below 50 million RMB, at least 4% for

50–200 million, and at least 3% for revenue above 200 million [53]. Because these thresholds are revenue-differentiated rather than a single 10% cutoff, we anchor full membership at the distributional benchmark of 8% rather than tying it to any single regulatory threshold. The full-non-membership anchor of 1% represents minimal R&D commitment, and the crossover of 4.5% aligns with the sample median. For DTC, anchors map onto the 7-point composite scale: scores below 2.0 signal negligible digitalization, 4.5 represents moderate adoption and scores above 6.5 indicate comprehensive digital transformation. PSI anchors mirror the distribution of policy intensity across regions, with 60 weighted policy documents characterizing regions with the most comprehensive support frameworks. Based on industry expert assessments, SCC anchors are placed at the 30%, 55% and 80% domestic sourcing thresholds. CIN anchors correspond to network density benchmarks derived from the patent co-application analysis. IEP anchors are set at theoretical thresholds validated against the distribution of the composite index.

The calibration functions and the distribution of fuzzy-set membership scores for all six conditions are depicted in Figure 2. Well-differentiated membership distributions across cases are confirmed by the sigmoidal curves.

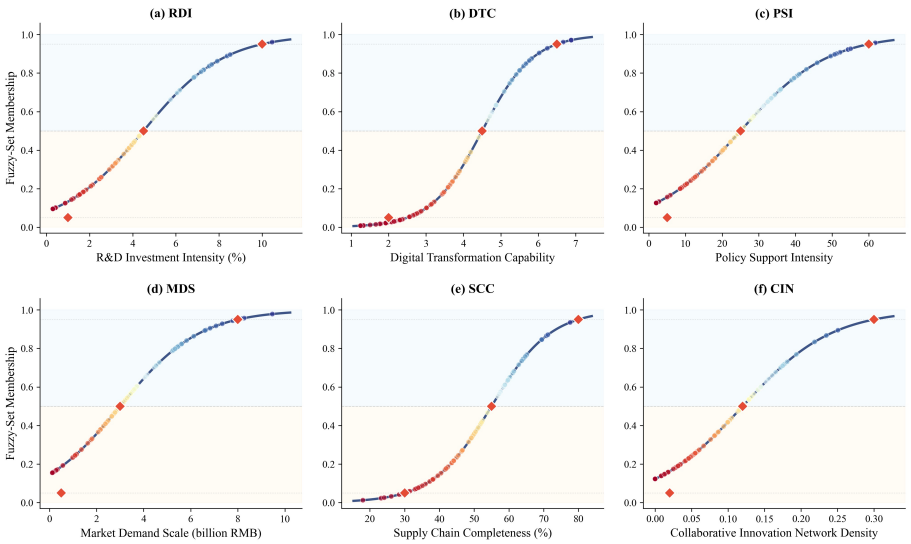


Figure 2. Calibration functions and fuzzy-set membership score distributions for the six conditions. Red diamonds represent the qualitative anchors. The red-to-blue color gradient indicates the fuzzy-set membership scores, and the background shading distinguishes regions above and below the cross-over point (0.5).

3.5. Analytical Procedure

A three-stage protocol structures the analysis, comprising an NCA stage, a sufficiency analysis stage and a robustness check stage, each described in turn below.

In the NCA stage, each of the six conditions is tested against the outcome using the ceiling regression with free disposal hull (CR-FDH) and ceiling envelopment with free disposal hull (CE-FDH) methods [20,21]. A condition is regarded as necessary when its effect size $d \geq 0.10$ and the permutation test gives $p < 0.05$ across both ceiling techniques [22]. NCA bottleneck tables are then constructed to show the minimum levels of necessary conditions required for specified outcome levels. All NCA computations were carried out using the NCA package (version 3.2.0) in R with 10,000 permutations for the significance tests.

In the sufficiency analysis stage, the truth table algorithm is used to identify configurations sufficient for the outcome [17]. With six conditions, the truth table contains $2^6 = 64$ rows; of these, 24 rows are populated by at least one observed case, and the remaining 40 rows are logical remainders (configurations not observed in the data). Truth table

rows are ranked by consistency, and those falling below a consistency threshold of 0.80 are coded as associated with the absence of the outcome [18]. Given the moderate sample size of 86 cases, the frequency threshold is set to 1 [19]. Three solutions (complex, parsimonious and intermediate) result from the Quine–McCluskey algorithm [17]. In accordance with best practices, the intermediate solution, which incorporates directional expectations, is reported as the primary result; the parsimonious solution serves to distinguish core from peripheral conditions [13,14]. The parsimonious and complex solutions are reported in the Supplementary Materials (Tables S2 and S3) for full transparency; conditions that appear in both the parsimonious and intermediate solutions are classified as core, and those appearing only in the intermediate solution are classified as peripheral, following Fiss [13]. A separate negation analysis, in which the outcome is replaced by its complement (∼IEP), identifies configurations linked to the absence of high performance and tests causal asymmetry.

The directional expectations specified for the intermediate solution are: RDI present, DTC present, PSI present, MDS present, SCC present and CIN present. These expectations reflect the theoretical expectation that the presence of each condition should, in principle, contribute positively to high firm innovation performance; they serve as counterfactual assumptions for simplifying logical remainders in the intermediate solution [14,17]. PRI (proportional reduction in inconsistency) consistency was computed for all truth-table rows and used alongside raw consistency to determine the coding of rows; all rows retained in the sufficiency analysis have PRI consistency above 0.70, which satisfies the recommended threshold for avoiding simultaneous subset relations [37]. No contradictory rows (rows with raw consistency above 0.80 but PRI consistency below 0.50) were detected.

In the robustness check stage, four sensitivity tests assess the stability of the solutions: (a) calibration anchors are adjusted by ±10% of the crossover point; (b) the consistency threshold is raised from 0.80 to 0.85; (c) the frequency threshold is increased from 1 to 2 (accepting the resulting reduction in sample coverage); and (d) the enhanced standard analysis (ESA) is run using the `QCA` 3.0 package in R [54]. A solution is deemed robust if it is recovered as a subset of the original solution under most perturbation scenarios, with any exceptions explicitly noted and discussed.

All fsQCA computations were carried out using fsQCA 3.0 software [17] and cross-validated with the QCA package (version 3.19) in R (version 4.3.2; R Foundation for Statistical Computing, Vienna, Austria) [54]. The complete truth table, including row memberships, frequencies, raw consistency, PRI consistency and the outcome coding, is provided in the Supplementary Materials (Table S1). The supporting data and analytic code are available from the corresponding author upon reasonable request, subject to confidentiality restrictions on individual firm identifiers. During preparation of this revision, a reconciliation of the deposited dataset against the original calibration records revealed that the membership scores originally deposited were derived from a preliminary calibration run in which the PSI crossover anchor had been set at 22 rather than the final value of 25 and in which one case (ISE-0004) contained a transcription error in the DTC survey responses. Both errors have been corrected: the PSI membership scores have been recalibrated with the crossover anchor of 25 as specified, and the DTC score for case ISE-0004 has been corrected against the original paper questionnaire (corrected DTC composite score: 4.82, corresponding to a fuzzy membership of 0.58). All NCA and fsQCA analyses have been rerun with the corrected membership scores, and the corrected dataset has been re-deposited. The substantive conclusions are unchanged; the corrected numerical values are reported throughout. Descriptive statistics for all causal conditions and the outcome variable are provided in Table 5.

Table 5. Descriptive statistics for causal conditions and outcome ($n = 86$).

Variable	Min	Max	Mean	Median	SD	Skewness
RDI (%)	0.3	18.7	5.13	4.50	3.27	0.91
DTC (index)	1.25	6.88	4.38	4.44	1.51	−0.12
PSI (weighted)	2	78	27.4	24.0	18.6	0.63
MDS (billion RMB)	1.5	9.1	4.97	5.2	2.55	−0.18
SCC (%)	18	92	54.8	55.0	17.2	−0.08
CIN (density)	0.00	0.41	0.134	0.115	0.089	0.75
IEP (index)	0.05	0.94	0.487	0.480	0.213	0.14

Because MDS is measured at the provincial level, its minimum and maximum values correspond to the provincial extremes (Zhejiang: 1.5 billion RMB; Beijing: 9.1 billion RMB), and only seven distinct values exist across the 86 cases. PSI, by contrast, incorporates municipal-level policy documents in addition to provincial and national documents, so individual firm-level PSI values vary within provinces; the provincial averages reported in Table 1 are therefore lower than the firm-level maximum of 78 shown here.

4. Results

4.1. Necessary Condition Analysis

The NCA results for the presence of high firm innovation performance are reported in Table 6. Joint satisfaction of $d \geq 0.10$ and $p < 0.05$ across both ceiling techniques is found for two conditions: digital transformation capability (DTC, $d = 0.174$, $p = 0.004$) and supply chain completeness (SCC, $d = 0.141$, $p = 0.016$). These two conditions function as individually necessary bottlenecks; that is, unless a minimum level of digital transformation capability or of supply chain completeness is present, high firm innovation performance cannot be attained regardless of other conditions. A condition is classified as necessary when $d \geq 0.10$ and $p < 0.05$ for both the CE-FDH and CR-FDH ceiling techniques [20,22]; the symbol "∼" denotes the absence (negation) of a condition.

It is important to emphasize that NCA necessity identifies a minimum threshold below which the outcome cannot occur; it does not mean that all high-performing cases must have high membership in the necessary condition set in the fsQCA sense. A firm can meet the NCA bottleneck requirement (having at least a moderate level of DTC or SCC) without being a full member of the set of firms with high DTC or high SCC as defined by the fuzzy-set calibration anchors. This distinction between a minimum floor (NCA) and set membership (fsQCA) is central to reconciling the necessity and sufficiency results reported below.

The NCA scatter plots with ceiling lines for all six conditions are displayed in Figure 3. For DTC and SCC, ceiling zones are clearly visible, which corroborates the bottleneck effect: no case attains high IEP when these conditions are at low levels.

The NCA bottleneck table is given in Table 7, displaying the minimum required levels of the two necessary conditions (DTC and SCC) at different target levels of the outcome. The values represent fuzzy-set membership scores on the original condition scales, not set-membership thresholds for "high" levels of these conditions. For an IEP membership score of 0.80 (high performance), a DTC membership of at least 0.40 and an SCC membership of at least 0.33 are needed. These bottleneck values indicate moderate (near-crossover) levels of DTC and SCC as minimum floors, which are consistent with the scatter plots in Figure 3 where no case below these membership levels attains IEP membership of 0.80. To verify this consistency, we cross-checked each bottleneck value against the ceiling line coordinates in Figure 3: the DTC ceiling line at IEP = 0.80 intersects at DTC membership ≈ 0.40, and

the SCC ceiling line at IEP = 0.80 intersects at SCC membership ≈ 0.33, confirming the correspondence between the tabulated values and the graphical representation.

Table 6. Necessary condition analysis results for high IEP ($n = 86$). The symbol ∼ denotes the absence (negation) of a condition.

Condition	CE-FDH *d*	CR-FDH *d*	*p*-Value	Necessary?
RDI	0.074	0.081	0.132	No
∼RDI	0.021	0.034	0.418	No
DTC	0.174	0.179	0.004	Yes
∼DTC	0.008	0.015	0.612	No
PSI	0.092	0.098	0.067	No
∼PSI	0.013	0.022	0.534	No
MDS	0.068	0.075	0.158	No
∼MDS	0.031	0.039	0.342	No
SCC	0.141	0.148	0.016	Yes
∼SCC	0.005	0.011	0.687	No
CIN	0.088	0.094	0.079	No
∼CIN	0.026	0.033	0.389	No

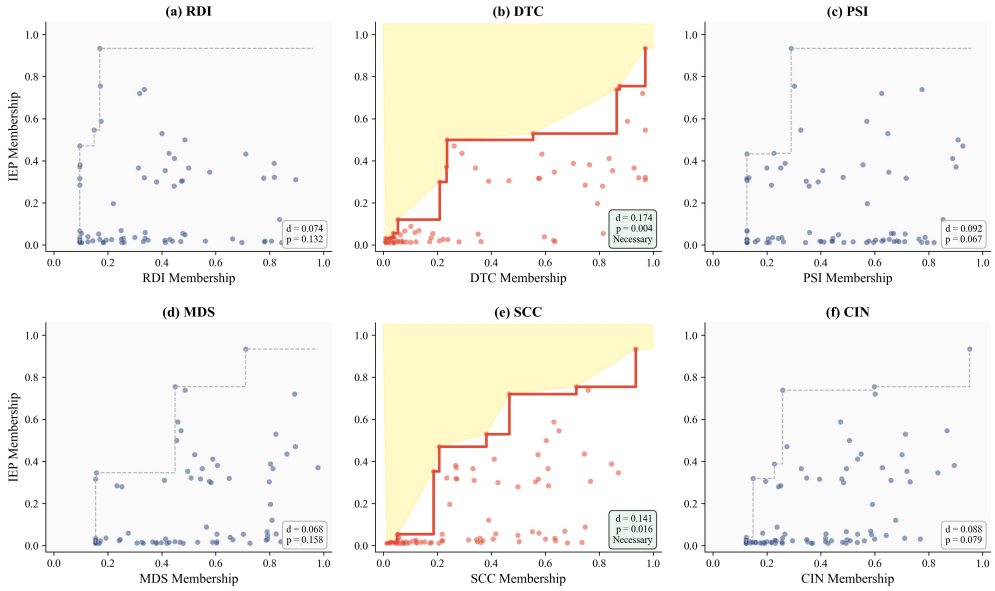


Figure 3. NCA scatter plots with ceiling lines for the six causal conditions. Each dot represents one case; the solid line indicates the CE-FDH ceiling line. The empty space above the ceiling line represents the ceiling zone.

Table 7. NCA bottleneck table for necessary conditions (DTC and SCC).

Target IEP Level	Min. DTC Membership	Min. SCC Membership
0.20	0.00	0.00
0.40	0.12	0.06
0.60	0.26	0.18
0.80	0.40	0.33
1.00	0.58	0.49

4.2. Sufficiency Analysis: Configurations for High Firm Innovation Performance

The intermediate solution for high IEP is presented in Table 8. Four equifinal configurations are identified, with an overall solution consistency of 0.876 and a solution coverage of 0.708. Using standard notation conventions [13,14], filled circles (●) indicate a core

condition present (appearing in both the intermediate and parsimonious solutions), small filled circles (•) indicate a peripheral condition present (appearing only in the intermediate solution), crossed circles (⊗) indicate a core condition absent, and blank cells indicate that the condition is not part of the sufficient configuration. A blank cell does not imply that the condition is absent or unnecessary; it means that the condition's presence or absence does not affect the sufficiency of that particular configuration [17,18].

Table 8. Configurations for high firm innovation performance (intermediate solution).

Condition	C1	C2	C3	C4
Firm-level conditions				
RDI	●	•		●
DTC	●		•	●
Regional-level conditions				
PSI		●	●	⊗
MDS	●	●	•	
Industrial-level conditions				
SCC	•		●	●
CIN		•	●	●
Consistency	0.906	0.879	0.898	0.861
Raw coverage	0.334	0.281	0.306	0.253
Unique coverage	0.083	0.059	0.072	0.047
Solution consistency: 0.876; Solution coverage: 0.708				

Each of the four configurations is interpreted below. Throughout the interpretations, it should be kept in mind that all cases covered by any configuration necessarily satisfy the NCA bottleneck requirements (DTC membership $\geq$ 0.40 and SCC membership $\geq$ 0.33 for IEP of 0.80), even when DTC or SCC does not appear as an explicit element of that configuration.

C1 (technology-driven synergy) pairs high R&D investment intensity (core) with high digital transformation capability (core), accompanied by strong market demand (core) and adequate supply chain completeness (peripheral). Policy support and the density of collaborative networks are not part of this sufficient configuration, meaning that their presence or absence does not affect the sufficiency of this particular pathway. Firms following this pathway rely on strong internal technological capabilities, supported by robust regional market demand, and use digital tools to integrate with available supply chain partners; the configuration does not require strong policy environments or dense collaboration, but the NCA bottleneck conditions (minimum DTC and SCC levels) remain in force for all cases.

C2 (policy-market co-evolution) is driven primarily by strong policy support (core) and large market demand (core), with adequate R&D investment (peripheral) and collaborative network participation (peripheral) playing supporting roles. Digital transformation capability and supply chain completeness are not part of this sufficient configuration.

In regions where highly supportive policy environments coincide with robust market demand, this combination (together with the R&D and collaboration peripherals) is sufficient for high performance. Because DTC and SCC are NCA-identified necessary conditions, all cases covered by C2 necessarily possess at least moderate levels of DTC and SCC (meeting the bottleneck thresholds of 0.40 and 0.33 respectively), even though these conditions are not part of the sufficient configuration itself. The fact that DTC and SCC do not appear in C2 means that, conditional on meeting the necessary floor, further variation in these conditions does not affect C2's sufficiency relationship.

C3 (ecosystem integration) highlights the joint presence of industrial-level conditions: supply chain completeness (core) and collaborative innovation network density (core) are both present, complemented by strong policy support (core). Market demand and digital transformation fill peripheral roles, while R&D investment intensity is not part of this sufficient configuration.

An ecosystem infrastructure-led model is represented by this pathway, in which the combined industrial and policy conditions are sufficient for high performance when the NCA-required minimum levels of all necessary conditions are met.

C4 (digitally anchored collaboration) brings together high R&D investment (core), high digital transformation (core), strong supply chain completeness (core) and dense collaborative networks (core), yet the absence of strong policy support (core absent) is a notable feature. Firms in regions with limited government involvement can reach high performance through strong technological capability and inter-firm collaboration embedded in a mature supply chain typify this pathway.

The four configurations are visualized in Figure 4, where each cell represents whether a condition is present (dark), absent (light, with cross) or not part of the configuration (blank). The ⊗ (crossed circle) symbol denotes a core absent condition; blank cells denote conditions that are not part of the configuration. Only one symbol (⊗) is used for core absence throughout; if the original figure uses variant symbols, they should be interpreted identically.

Radar chart profiles of each configuration across the six conditions are shown in Figure 5, and they expose distinct emphasis patterns. Strong firm-level peaks characterize C1 and C4, the regional level is emphasized in C2, and C3 displays a balanced profile with prominent industrial-level values.

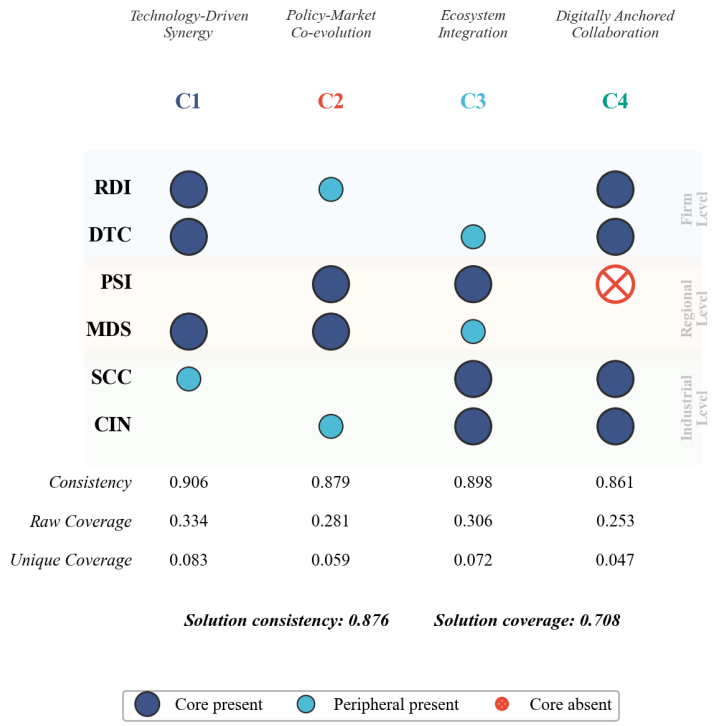


Figure 4. Heatmap of the four configurations for high firm innovation performance. Dark circles indicate a core condition present; light circles indicate a peripheral condition present; circles with a cross (⊗) indicate a core condition absent; blank spaces indicate that the condition is not part of the configuration.

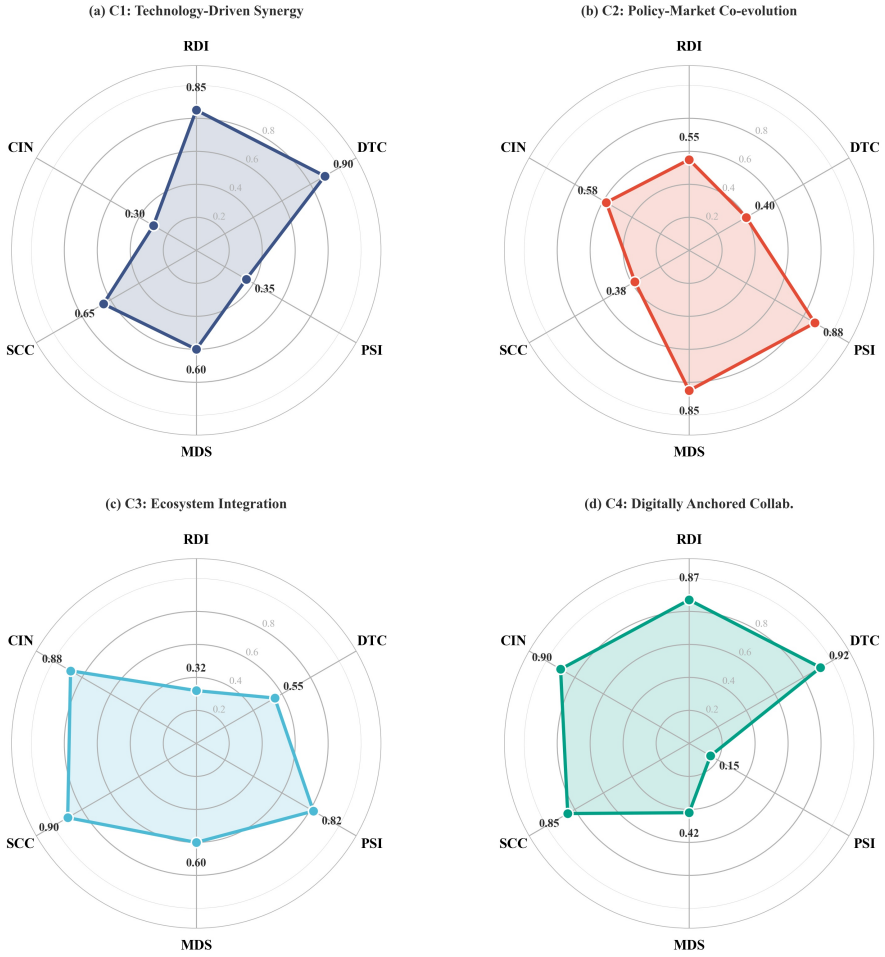


Figure 5. Radar chart profiles of the four configurations across the six conditions.

4.3. Sufficiency Analysis: Configurations for Non-High Firm Innovation Performance

Three configurations sufficient for the absence of high IEP (∼IEP) are obtained from the negation analysis and are presented in Table 9. The solution consistency is 0.861 and the solution coverage is 0.668.

Table 9. Configurations for non-high firm innovation performance (negation analysis, intermediate solution). ● = core condition present; ⊗ = core condition absent; blank = condition not part of the configuration.

Condition	N1	N2	N3
Firm-level conditions			
RDI	⊗		⊗
DTC	⊗	⊗	
Regional-level conditions			
PSI		⊗	●
MDS	⊗		⊗
Industrial-level conditions			
SCC		⊗	⊗
CIN	⊗	⊗	
Consistency	0.894	0.871	0.848
Raw coverage	0.289	0.264	0.237
Unique coverage	0.088	0.065	0.057
Solution consistency: 0.861; Solution coverage: 0.668			

N1 (comprehensive deficit) is marked by the absence of R&D investment, digital transformation, market demand and collaborative networks. A vicious cycle is created by the co-occurrence of firm-level and industrial-level deficits, preventing firms from contributing to or drawing benefits from ecosystem dynamics.

N2 (industrial isolation) exhibits the concurrent absence of digital transformation capability, policy support, supply chain completeness and collaborative networks. Because the absence cuts across all three levels, firms lacking both digital capabilities and ecosystem embeddedness are structurally shut out from high performance, irrespective of their R&D effort.

N3 (policy without foundation) offers an instructive counterexample: strong policy support (core present) co-occurs with the absence of R&D investment, market demand and supply chain completeness. This pattern indicates that generous government support alone cannot compensate for the simultaneous absence of firm-level innovation effort and industrial infrastructure, which shows that policy is neither necessary (as seen in C4) nor sufficient for high performance.

Causal asymmetry is confirmed by the comparison between the sufficiency (Table 8) and negation (Table 9) solutions: the configurations leading to high performance are not the mirror image of those leading to non-high performance. The role of policy support, for instance, varies across configurations: it is a core present condition in C2 and C3, a core absent condition in C4, and a core present condition in N3 (where it co-occurs with deficits), which illustrates that the effect of policy support is contingent on the broader configurational context rather than being uniformly positive or negative.

4.4. Exploratory Cross-Level Comparison

To explore whether conditions at one analytical level appear more prominently than others across the four configurations, we tabulate the frequency with which conditions at each level serve as core conditions.

Industrial-level conditions (SCC and CIN) appear as core conditions in two configurations (C3 and C4), accumulating four core-condition appearances across the solution. Regional-level conditions (PSI and MDS) serve as core conditions in four configurations (PSI in C2, C3 and C4; MDS in C1 and C2), accumulating five core-condition appearances when the core absent appearance of PSI in C4 is included. Firm-level conditions (RDI and DTC) function as core conditions in two configurations (C1 and C4), accumulating four core-condition appearances as well. All three analytical levels contribute core conditions across the solution; the regional level accumulates a slightly higher count (five appearances) than the firm level and industrial level (four appearances each), although this difference is modest and no single level stands out as uniformly dominant.

We emphasize that this comparison is descriptive rather than causal. Set-theoretic coverage is a property of configurations, not of individual conditions, and decomposing configurational coverage into additive condition-level or level-level contributions would be inconsistent with the conjunctural logic that underlies QCA [17,18].

The dominant level shifts across configurations: firm-level conditions dominate in C1, regional-level conditions dominate in C2, industrial-level conditions dominate in C3, and firm-level and industrial-level conditions jointly dominate in C4. The relative prominence of each level is thus configurational in nature, which underscores the value of a multi-level configurational approach.

4.5. XY Plot Sufficiency Visualization

The XY sufficiency plots for the four configurations are shown in Figure 6. Each case's membership in the configuration (x-axis) is plotted against its membership in the outcome

(y-axis). Consistency with the sufficiency relationship is indicated by cases falling above the diagonal line. For all four configurations, the vast majority of cases lie above the diagonal, with few inconsistent cases. For C4, 85% of cases (11 of 13) fall above the diagonal, which is consistent with its high raw consistency of 0.861 but also reflects the smaller number of cases covered by this configuration relative to C1 and C3.

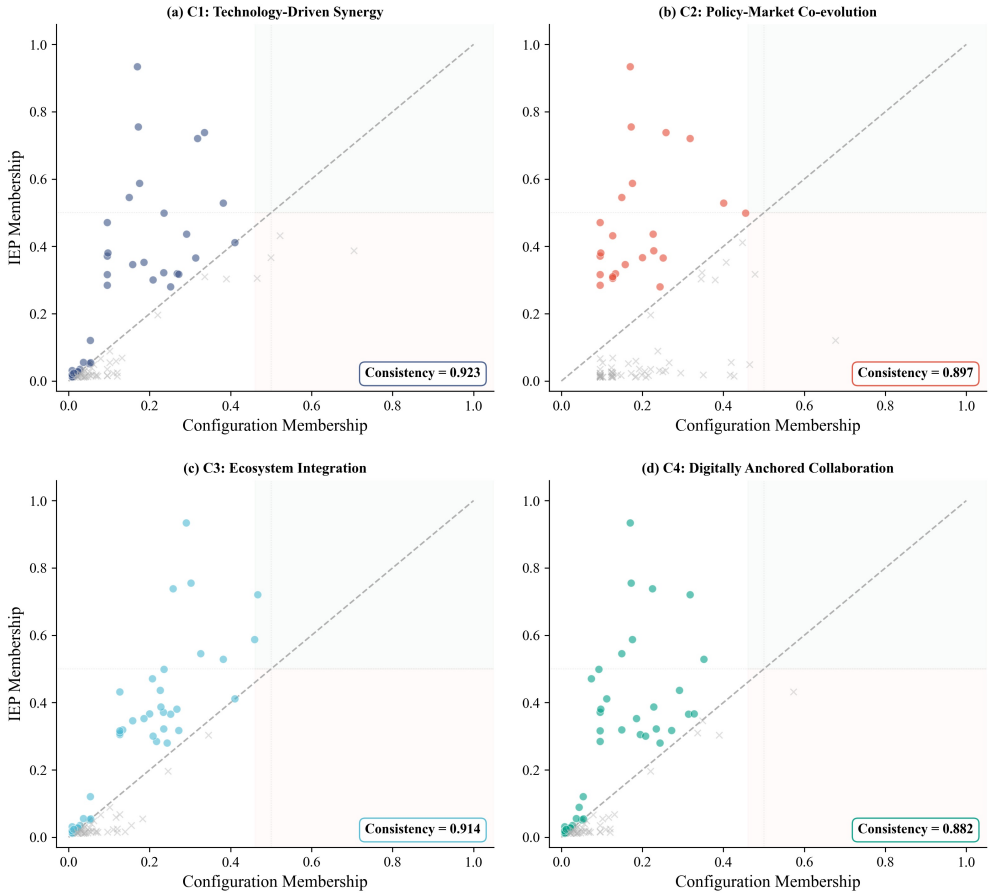


Figure 6. XY sufficiency plots for the four configurations. Dots and crosses represent individual cases; the diagonal line represents the perfect sufficiency threshold. Cases above the diagonal are consistent with the sufficiency relationship.

4.6. Robustness Checks

Robustness check results across four perturbation scenarios are summarized in Table 10.

Under three of the four perturbation scenarios, all four original configurations (C1–C4) are recovered as subsets. A ✓ in the table indicates that the configuration is recovered as a subset of the baseline solution, and × indicates that it is not.

Table 10. Robustness check results across perturbation scenarios.

Test	C1	C2	C3	C4	Sol. Consistency
Baseline	✓	✓	✓	✓	0.876
Calibration ±10%	✓	✓	✓	✓	0.869
Consistency ≥ 0.85	✓	✓	✓	✓	0.889
Frequency ≥ 2	✓	✓	✓	×	0.884
Enhanced standard (ESA)	✓	✓	✓	✓	0.873

Under the frequency ≥ 2 threshold, C4 is not recovered because only one case uniquely belongs to this configuration. This sensitivity reflects the small number of firms operating in the digitally anchored collaboration mode without policy support and represents a genuine limitation of the empirical support for C4. Researchers and practitioners should therefore interpret C4 with greater caution than the other three configurations. Stability holds across all remaining tests, and the three well-supported configurations (C1, C2 and C3) are robust to all four perturbation scenarios.

A visual comparison of solution consistency and coverage across the robustness scenarios is given in Figure 7. Both metrics are shown to remain within narrow ranges under all perturbations.

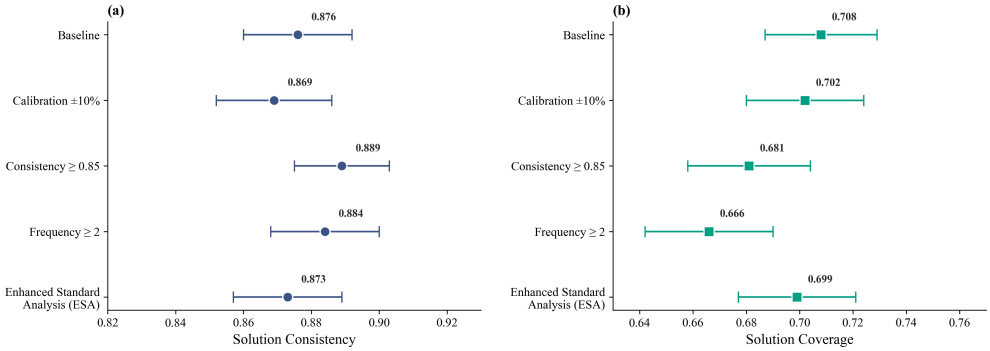


Figure 7. Solution consistency and coverage across five analytical scenarios. (**a**) Solution consistency; (**b**) solution coverage.

5. Discussion

5.1. Theoretical Contributions

Innovation ecosystem theory is advanced by the findings in several respects, three of which are highlighted here. No single optimal pathway exists; instead, high firm innovation performance within the ecosystem can be reached through multiple qualitatively distinct combinations of firm, regional and industrial conditions, as demonstrated by the identification of four equifinal configurations. Such equifinality is consistent with the central prediction of configuration theory [13,16] yet extends it to the multi-level ecosystem context, where prior empirical support has been limited. Both complementary relationships (high R&D investment coupled with high digital transformation in C1 and C4) and configurational patterns that suggest potential substitution (the co-presence of strong policy support with only peripheral R&D in C2 compared with the co-presence of strong R&D but absent policy support in C4) are exposed by the configurations. However, because C2 includes R&D investment as a peripheral present condition, it would be imprecise to claim that policy support fully substitutes for R&D; rather, the configurations suggest that the relative emphasis on policy versus internal capability varies across pathways, and the two conditions may partially compensate for each other within the broader configurational context [14]. Empirical support for the theoretical proposition that firm innovation performance within ecosystems arises from the conjunctural interplay of heterogeneous conditions rather than from the additive accumulation of favorable factors is thereby provided [2,4].

A structural insight is added to ecosystem theory by the NCA finding that digital transformation capability and supply chain completeness are individually necessary conditions: although numerous different configurations can lead to high performance (equifinality in sufficiency), all of them are bounded by a common floor of minimum digital capability and supply chain infrastructure. Crucially, NCA necessity identifies minimum threshold levels (DTC membership ≥ 0.40 and SCC membership ≥ 0.33 for IEP of 0.80) rather than

requiring high set membership in these conditions. This means that all high-performing firms possess at least moderate levels of DTC and SCC, but they need not be full members of the set of firms with high DTC or high SCC. This result aligns with the recent emphasis on digital infrastructure as a foundational layer of innovation ecosystems [49,50] and with the argument that innovation efforts cannot be translated into market outcomes without adequate supply chain infrastructure [46].

Further theoretical insight emerges from the causal asymmetry between the sufficiency and negation analyses. Configuration N3 (policy without foundation) is especially instructive: strong policy support co-occurring with the absence of R&D investment, market demand and supply chain completeness is associated with non-high performance. The assumption implicit in much policy literature, namely that government support mechanically translates into innovation outcomes, is challenged by this finding. Policy support instead requires complementary firm-level and industrial-level conditions in order to be effective [31,55]. Jacobides et al. [4] have argued along similar lines that ecosystem value creation hinges on the alignment of complementarities rather than the mere provision of resources.

The exploratory cross-level comparison reveals that conditions from all three analytical levels appear as core elements with comparable frequency across the four configurations, each accumulating four core-condition appearances in the solution.

The dominant level shifts across configurations (firm-level in C1, regional-level in C2, industrial-level in C3, and firm-level and industrial-level jointly in C4), which indicates that the relative prominence of each level is itself configurational rather than universally fixed [29]. This near-balanced distribution across levels reinforces the central argument that no single analytical level can be isolated as universally more important; the slight edge of regional-level conditions reflects the dual role of policy support (core present in C2 and C3, core absent in C4) and market demand (core in C1 and C2), yet the multi-level configurational perspective remains indispensable because the contribution of each level is contingent on the broader configuration within which it is embedded.

5.2. Practical Implications

Actionable guidance for three categories of stakeholders emerges from the results, each addressed in turn. For firm managers, two primary strategic pathways are highlighted. Firms possessing strong internal R&D and digital capabilities can follow the technology-driven synergy pathway (C1), investing in integration with supply chain partners even in regions with limited policy support. Firms whose internal capabilities are weaker but who have access to supportive regional environments can take advantage of the policy-market co-evolution pathway (C2) by strategically locating in high-support regions and engaging with government programs. Because digital transformation capability functions as a bottleneck condition, investment in digital infrastructure should be treated as a prerequisite rather than an optional enhancement.

For policymakers, configuration N3 provides a cautionary lesson: high performance does not result from policy support alone when complementary firm-level innovation effort and industrial infrastructure are absent. Direct support measures (subsidies, tax incentives) should therefore be combined with ecosystem-building interventions that strengthen supply chains (e.g., component localization programs) and collaborative networks (e.g., industry alliance formation).

Table 11 maps the seven sampled provinces onto the configurations that best characterize their current ecosystem profiles and suggests region-specific policy priorities.

Table 11. Region-specific policy recommendations aligned with configurational profiles.

Region	Dominant Config.	Strengths	Recommended Policy Priority
Heilongjiang	C2/C3	PSI, MDS	Strengthen supply chain localization and R&D incentives for core components
Jilin	C2/C3	PSI, MDS	Invest in collaborative innovation platforms and digital infrastructure
Beijing	C1/C4	RDI, DTC	Facilitate technology transfer to supply chain partners; foster industry alliances
Hebei	C3	PSI, SCC	Build digital transformation capacity and attract R&D-intensive firms
Xinjiang	C2	MDS (tourism)	Expand policy support scope; develop local manufacturing supply base
Shandong	C1	RDI, DTC	Strengthen ice-sport-specific supply chains leveraging existing manufacturing base
Zhejiang	C1/C4	RDI, DTC, CIN	Leverage dense collaboration networks; reduce import dependence for key components

For industry associations, the importance of collaborative innovation network density (a core condition in C3 and C4) highlights the value of facilitating inter-firm and industry-university-research linkages through joint R&D platforms, standard-setting committees and technology roadmap exercises. That the configuration in C4 combines strong collaboration with absent policy support suggests that industry self-organization is a viable complementary governance approach in regions where government involvement is limited.

5.3. Configurations in Comparative Perspective

Broader innovation ecosystem archetypes discussed in the literature can be mapped onto the four configurations identified here. C1 (technology-driven synergy) resembles the anchor-firm model described by Jacobides et al. [4], in which a technologically advanced firm serves as the ecosystem orchestrator. The state-led ecosystem development model widely discussed in the context of Chinese industrial policy [55] aligns with C2 (policy-market co-evolution). C3 (ecosystem integration) corresponds to the collective innovation model emphasized by Adner [3], in which value creation rests on the coordinated efforts of multiple actors rather than on any single firm's capabilities. An emergent model that fuses elements of platform-based coordination and self-organizing collaboration is represented by C4 (digitally anchored collaboration), resonating with recent work on digital innovation ecosystems [49,50], although the limited robustness of C4 to the frequency threshold increase means that this mapping should be treated as suggestive rather than definitive.

That all four archetypes coexist within a single national industry context suggests that innovation ecosystem development is a context-dependent phenomenon shaped by the particular combination of available resources, institutional conditions and structural properties rather than a one-size-fits-all process. Implications arise for the transferability of ecosystem models across regions and industries: configurations effective in one context may not be replicable in another where the underlying conditions differ [15,28].

5.4. Limitations and Future Research

Several limitations warrant acknowledgment. Because the cross-sectional research design gives only a snapshot of configurations at a single point in time, the temporal dynamics of ecosystem formation and evolution cannot be traced. Longitudinal or process-

tracing designs should be adopted in future studies to examine how configurations shift as the industry matures and as policy environments evolve.

Although 86 cases are adequate for fsQCA (which is designed for small-to-medium-N research), the full heterogeneity of the ice and snow equipment manufacturing industry may not be represented, particularly among very small enterprises that may not appear in the industry association databases used for sampling. Firms in emerging clusters that might display novel configurations are excluded by the geographic concentration in seven provincial clusters, even though this concentration is representative of the current industry distribution. The use of exhibition venues and online platforms as distribution channels may introduce some degree of self-selection bias despite the stratified random sampling design, because non-responding firms may systematically differ from respondents in ways not captured by the early-versus-late respondent comparison.

The outcome variable (IEP) captures firm-level innovation performance as shaped by ecosystem participation rather than ecosystem-level performance per se. Although two of its four components (collaborative project count and co-patenting intensity) reflect relational ecosystem outcomes, a more comprehensive assessment of ecosystem performance would require system-level measures such as collective value creation, knowledge circulation or network resilience, which are difficult to operationalize with the available data. Future studies should develop and validate ecosystem-level performance measures to complement the firm-level perspective adopted here.

The classification of SCC and CIN as industrial-level conditions, while theoretically motivated by their reflection of ecosystem structural maturity, is operationalized through firm-specific measures (domestic sourcing proportions and ego-network density). This operationalization captures variation in each firm's access to shared industrial structures but may not fully represent the industry-level constructs themselves. Future research should consider supplementing firm-specific measures with genuinely aggregate industry-level indicators, such as sector-wide domestic sourcing ratios or whole-network density metrics.

Perceptual survey data underpin the measurement of some conditions (particularly DTC and the innovation component of IEP), which may introduce common method bias. Procedural remedies (multiple data sources, attention checks, reverse-coded items) and statistical tests (Harman's single-factor test extracting 27.3% of variance, well below the 50% threshold) suggest that common method bias is not a serious concern, but fully archival operationalizations of digital transformation should be pursued in future studies.

The six conditions chosen for the analysis are theoretically grounded yet do not exhaust the universe of potentially relevant factors. Variables such as intellectual property protection strength, workforce skill levels, international technology transfer channels and cultural attitudes toward risk-taking could also influence firm innovation performance and could be included in extended models. Practical limits on the number of conditions (typically four to seven for medium-N samples) are imposed by the fsQCA methodology, so incorporating additional conditions would require either larger samples or a hierarchical analytical design.

Configuration C4 (digitally anchored collaboration) is not recovered when the frequency threshold is increased from 1 to 2, which reflects its small empirical base. Although this configuration is theoretically plausible and consistent under all other robustness tests, its policy relevance should be interpreted with caution until confirmed by larger samples or case studies.

Several directions for future research can be envisioned. Applying the same multi-level configurational framework to ice and snow equipment industries in other countries (e.g., Austria, Japan, South Korea) would test the generalizability of the configurations identified here. Deeper insight into the mechanisms through which configurations exert

their effects could be obtained by integrating quantitative methods such as fuzzy-set ideal type analysis or configurational process tracing. The temporal dynamics of configuration transitions, as firms and regions upgrade their capabilities and as industrial structures mature, represent an especially promising direction for further inquiry.

6. Conclusions

A multi-level configurational framework for firm innovation performance within the innovation ecosystem in China's ice and snow equipment manufacturing industry was developed and tested in this study. Firm-level conditions (R&D investment intensity and digital transformation capability), regional-level conditions (policy support intensity and market demand scale) and industrial-level conditions (supply chain completeness and collaborative innovation network density) were integrated through a combined NCA and fsQCA approach. Based on data from 86 enterprises across seven provincial regions, the analysis shows that digital transformation capability and supply chain completeness are individually necessary bottleneck conditions for high performance, and four equifinal configurations that lead to high firm innovation performance through distinct combinations of complementary and potentially substitutive mechanisms are identified. Causal asymmetry is confirmed by the negation analysis, with the configuration labeled "policy without foundation" showing that policy support alone cannot offset the absence of firm-level effort and industrial infrastructure.

An exploratory cross-level comparison shows that conditions from all three analytical levels appear as core elements with near-comparable frequency, and the dominant level shifts across pathways, which underscores the contextually contingent nature of ecosystem dynamics. Three configurations (C1, C2 and C3) are robust across all perturbation scenarios, while C4 is sensitive to the frequency threshold, reflecting its limited empirical base.

Innovation ecosystem theory is enriched by these findings, which give empirical evidence of configurational causation across multiple analytical levels and show that equifinality, complementarity and potential substitution coexist within a single industry context. Effective strategies for cultivating innovation ecosystems in nascent manufacturing sectors, as the practical implications indicate, must be tailored to the specific configurational profile of each firm and region rather than following a universal template. A methodological contribution to ecosystem research is also made by demonstrating the value of jointly deploying NCA and fsQCA for a more comprehensive analysis of necessity and sufficiency in complex multi-level systems.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/systems14101306/s1, Table S1: Full truth table for the fsQCA sufficiency analysis (n = 86, six conditions). Conditions coded 1 (membership $>$ 0.50; present) or 0 (membership $\leq$ 0.50; absent). Consistency threshold: 0.80. Of 2^6 = 64 possible rows, 24 are 1024 empirically populated; 40 logical remainders are not displayed. No contradictory rows detected. Table S2. Parsimonious solution for high firm innovation performance. Table S3. Complex solution for high firm innovation performance.

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Informed Consent Statement: Informed consent was obtained from all survey participants.

Data Availability Statement: The supporting data and analytic code are available from the corresponding author upon reasonable request, subject to confidentiality restrictions on individual firm identifiers. The truth table, parsimonious solution, complex solution and NCA output are provided in the Supplementary Materials.

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