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How Do Clusters Drive Firm Performance in the Regional Innovation System? A Causal Complexity Analysis in Chinese Strategic Emerging Industries

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Abstract: From a configurational perspective, this study aims to explain how clusters drive firm performance in the regional innovation system by considering the relationship between cluster and firm performance as causal complexity. Using an original dataset comprising 292 Chinese firms in strategic emerging industries (SEIs), this study employs a fuzzy set qualitative comparative analysis (fsQCA) to investigate the conjunction effects of interorganizational dependence, network embeddedness, and ambidextrous innovation on cluster firms' performance. The results showed that the fsQCA method uncovers causal combinations of these cluster factors that lead to high performance. These configurations imply two alternative pathways to enhance performance, where exploitative innovation is identified as the core causal condition.

Keywords: strategic emerging industries; cluster's collaborative innovation; ambidextrous innovation; network embeddedness; interorganizational dependence

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1. Introduction

In today's knowledge economy, industrial clusters have been proven to be key determinants of firm performance in the regional innovation system [1]. A cluster is a geographic concentration of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions in particular fields that compete but also cooperate [2]. Cluster firms are those organizations in a cluster. In industrial clusters, multiple linkages and geographic proximity are two fundamental characteristics [3] Establishing both vertical and horizontal links with other firms and associated institutions geographically localized [4] brings various benefits to all members in an industrial cluster, such as agglomeration economies, improved productivity, better knowledge sharing and collaborative innovation, and can better adapt to a more complex and turbulent technological environment [5–10]. Such advantages of clusters are especially salient and critical for firms in strategic emerging industries (SEIs). The development patterns and trajectories of SEIs are significantly shaped by emerging technologies. These technologies, such as wind deflecting turbines, bioinformatics, 3D printing, and artificial intelligence, have become increasingly "intelligent" [11]. They dramatically affect both innovation and organizing processes in SEIs [12,13]. Firms largely rely on intra- and extra-cluster linkages to break financial, infrastructural, and managerial constraints [8], build greater production and innovation capabilities in SEIs [14], and efficiently mobilize and gather diverse resources and knowledge for recombination, a vital source of innovative breakthroughs in SEIs [15]. Therefore, industrial clusters have become one of the fundamental drivers of innovations in SEIs by boosting the networking of firms in SEIs and fostering collaboration beyond geographic boundaries [8].

Generally, the literature on cluster innovation proposes that the cluster mainly influences organizational outcomes through agglomeration and network effects [8,16]. The agglomeration effect emphasizes the role of geographic embeddedness of clusters [17], arising from spatial and organizational proximity of the co-location of firms [18]. On the contrary, the network effect stresses the benefits of the relational and structural embeddedness of clusters. This effect likely occurs when the collaborative innovation network becomes dense and multi-connected and has homophily features [19,20].

By considering these two kinds of clustering effects, existing research has examined how clusters drive firm outcomes from multiple perspectives, such as a resource-based view, network embeddedness, open innovation, and dynamic capabilities [21]. In addition, these studies have explored various factors in the regional innovation system that influence the relationship between cluster and firm-level outcomes. These factors include the characteristics of an organization (e.g., organizational isomorphism, organizational proximity) [22], the knowledge creation and transfer processes in which scholars have paid specific attention to knowledge sharing, ambidextrous learning, and absorptive capability [8,23,24], and the relational and structural aspects of the collaborative networks where the firms are embedded [25,26].

The relationship between cluster and firm outcomes has received considerable academic attention over recent decades [21,27]. However, there are disagreements on some research issues, such as whether a specialized or ambidextrous organization produces more innovative outcomes in clusters [28,29] and if more network embeddedness always leads to better firm performance in clusters [30].

On the one hand, the literature on ambidexterity theory stresses the significant role of pursuing exploration and exploitation simultaneously in achieving a sustainable competitive advantage [31]. In this dominant view, ambidexterity is generally beneficial to firm performance since it enables firms to fully leverage the "synergistic fusion of exploration and exploitation" [32] (p. 1287). That is, exploration and exploitation could reinforce each other to improve firm performance [33]. Such complementarity can be a vital driving force of organizational performance [34].

However, ambidexterity can also jeopardize firm performance [35]. Due to the antagonistic nature of exploration and exploitation, tensions between these two activities are difficult to resolve, especially when firms face resource constraints and such balancing efforts are costly [36]. In addition, the trade-offs between these conflicting activities are reinforced by path dependencies [37]. In this scenario, to achieve ambidexterity, firms need to build complex routines, which may negatively affect firm performance [38]. Finally, resource interdependence may hinder the effectiveness of ambidexterity in improving firm performance since it increases complexity and uncertainty in pursuing both exploration and exploitation [32]. Therefore, to effectively enhance performance, exploration or exploitation should be specialized [39]. Such a benefit of specialization is topically significant in the context of clusters where firms can outsource exploitative or explorative activities to their cluster partners [29].

On the other hand, the literature has widely acknowledged the positive effects of network embeddedness on cluster firms' performance (e.g., [40]). However, a few studies reveal that excessive network embeddedness may undermine performance, since overwhelming network ties could damage knowledge diversity [41] and restrict the reputation benefits of firms in a central position of cluster network [42].

In these relevant studies, there are disagreements about the relationship between cluster factors and firm performance, yet it is important to note that these cluster factors are interrelated, and different aspects of them will affect firm performance differently. Thus, we believe that it is possible to reconcile the multiple effects of various cluster factors by considering a systematic analysis of their combined effects on firm performance. However, such an analysis has not been well explored, either in terms of research subjects or methods. Few empirical studies have explored this issue (one exception is [9]), although a recent literature review suggested that researchers should consider high interdependence among different factors that contribute to ambidexterity or cluster innovation for better performance [21,43]. For example, resource sharing and knowledge transfer have become driving factors for the formulation of collaborative relationships in clusters [44]. However, the synergistic effects of these two factors largely depend on the interactions among firms within and across clusters [45]. The more interactions between firm clusters, the greater the combined impact of these two factors. Therefore, our research is unique in that it explores specific combinations of multiple cluster factors that enable firms to gain high performance.

In addition, multiple alternative pathways have not been well investigated for cluster firms to achieve high-performance outcomes [46]. One of the reasons is the limitation of traditional research methodologies, especially the correlational approach predominantly adopted in this field [47]. Such a method attempts to explain the organizational outcome by considering the net effects of different factors on firm performance in clusters separately. However, the relationship between cluster and innovation outcome is complex [9,48], and is also known as causal complexity. To address this issue, from the view of configuration, we explore a novel method named fuzzy set qualitative comparative analysis (fsQCA) to uncover the equivalent multidimensional pathways that can result in high performance of cluster firms.

To do so, our research aims to answer the following exploratory research question: what configurations of inter-organizational interdependence, network embeddedness, and ambidextrous innovation are associated with the high-level performance of cluster firms? We also examine and validate this question in the context of China since it has become the largest emerging market and made huge progress in establishing industrial clusters for SEIs development during this decade [49].

Our study contributes to the literature in two critical ways. First, drawing on a configurational approach, we provide a comprehensive and integrative theoretical framework for understanding collaborative innovation in clusters by combining resource dependence theory, social embeddedness theory, and ambidexterity theory. Such a unique framework sheds additional light on building both cluster ambidexterity and cluster innovation capability.

Second, by applying the fsQCA methodology to a sample of cluster firms gathered in Chinese SEIs, we further explain how clusters drive firm performance from the conjunctural and equifinal relations among multiple cluster factors. Accordingly, we address the inconsistent conclusions drawn from ambidexterity theory and social network theory. Our study explores these debates in the context of industrial clusters and identifies boundary conditions under which ambidexterity or network embeddedness can more effectively improve firm performance.

Taken together, this research paves the way for future explorations on how managers can promote firm performance in industrial clusters via different pathways. This is also beneficial for accelerating the cultivation and development of SEIs in emerging economies.

2. Theoretical Development

From a configurational perspective, our research tries to provide a richer understanding of the interaction between multiple cluster factors and firm performance, and thereby advances the cluster innovation literature. Particularly, we inductively explore necessary and sufficient conditions in different configurations that lead to high performance. According to [50], such a configuration perspective is quite useful in explaining causal complexity phenomena (e.g., paths of achieving superior firm performance) by identifying different combinations of coherent causal conditions for a given outcome.

Then, based on the relevant literature, we identify interorganizational interdependence, network embeddedness, and ambidextrous innovation as three key cluster factors that significantly affect firm performance. In our study, to better represent these factors, six influential theoretical constructs are adopted, including resource interdependence, task interdependence, local embeddedness, non-local embeddedness, exploitative innovation, and exploratory innovation. We then propose alternative holistic archetypes from these theoretical constructs emerging from Resource Dependence Theory (e.g., [51,52]), Social Network Theory (e.g., [26,53,54]), and Ambidexterity Theory (e.g., [23,28,29,55]).

Figure 1 shows the conditions and their six constructs used to form configurations that explain the drivers of firm performance in clusters. This configurational approach puts deep insights into how the presence or absence of these conditions in different configurations can lead to the same outcome. In this way, our study uncovers that cluster firms can achieve high performance through different pathways. Based on the framework in Figure 1, we propose that the interactions among these conditions can exhibit complementary or substitution effects on improving firm performance and these effects mainly depend on the arrangement of such conditions. We hence seek to identify specific configurations of those six theoretical constructs to formulate empirically validated performance-enhancement strategies in clusters. In the following sections, we detail the key conditions in Figure 1 and discuss their potential impacts on firm performance.

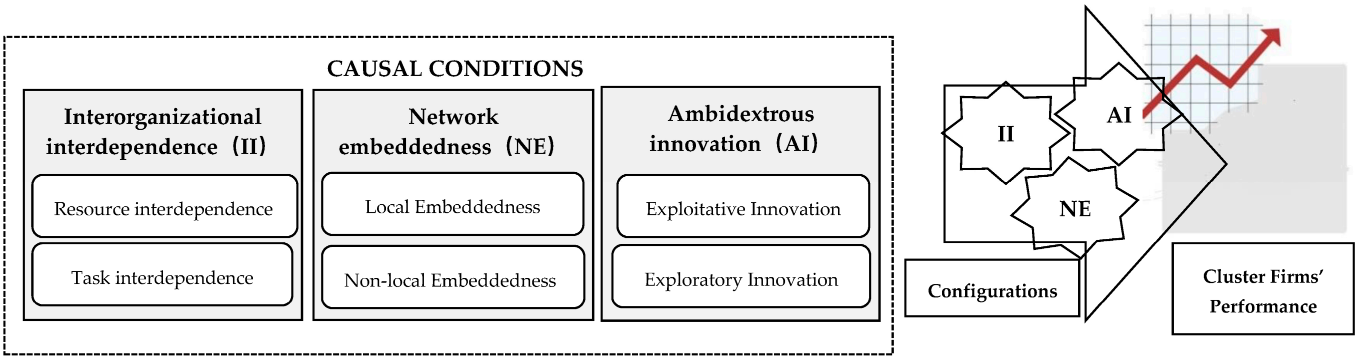

Figure 1. A configurational model of causal conditions and performance in clusters.

2.1. *Interorganizational Interdependence and Firm Performance in Clusters*

Past studies mainly adopt resource dependence theory (RDT) to explore inter-organizational interdependence among firms. RDT suggests firms are "constrained by a network of interdependencies with other organizations" [56] (p. 26). These interdependencies, which arise from the social relationships of organizations embedded in networks [57], are the key determinants for firm strategic actions to overcome resource scarcity [51]. Particularly, RDT emphasizes that firms rely on the formation of interorganizational arrangements (e.g., alliances, joint ventures) to manage interorganizational interdependence with other organizations and to mitigate environmental uncertainties and resource constraints [51]. As a result, RDT provides a useful theoretical framework for explaining how organizations acquire resources through adopting an interorganizational cooperation strategy and that acquiring resources in this way may potentially influence organizational performance [52]. From this aspect, RDT can be seen as a theory of organizational performance [58].

In the context of clusters, such interorganizational interdependence could affect firm performance in several ways. First, following a logic of embeddedness, mutual dependence fosters inter-organizational relations or connections (e.g., alliance) in clusters [59]. These increasing cluster linkages help firms accelerate innovation speed by leveraging the partners' complementary resources and technologies [8].

Second, interorganizational interdependence may weaken mutual substitutability and advance the commitment and reciprocity of firms [59]. Such effects can stabilize the flow of resources and improve resource control to strengthen a firm's market power [51]. Third, interorganizational interdependence has been found to significantly affect firm performance by stimulating the coordination of activities (e.g., joint action) among exchange partners [60]. For instance, the empirical study of [61] on U.S. automotive manufacturers shows that joint action positively impacts performance. Finally, managing external interorganizational dependence may require firms to seek ownership-based arrangements, as these arrangements enable firms to enjoy relational advantages that facilitate the sharing of learning among organizations in cluster collaboration [62].

2.2. Ambidextrous Innovation and Firm Performance in Clusters

From the perspective of organizational learning, ambidexterity theory offers an exploration–exploitation framework for understanding how an organization achieves both short- and long-term competitive advantages [31]. Such a framework stresses that firms must leverage existing knowledge and routines (exploitation) and pursue new knowledge and technologies (exploration) simultaneously. Hence, ambidexterity is vital for organizational survival and superior organizational performance [37].

However, exploration and exploitation are two different types of innovation activities that create conflicting tensions [63,64]. Exploitative innovations refer to incremental improvements in existing products and processes, emphasizing refinement, efficiency, and stability [33,63]. By contrast, exploratory innovations are always accompanied by risk-taking, discovery, and variation, and are related to the development of new processes and products [65]. Since these two activities have very different capability requirements, firms often face an ambidextrous challenge of balancing exploitation and exploration [23,66]. In the scenario of clusters, such a challenge also highlights the trade-offs stemming from "combining internal and external technology sourcing" [31] (p. 692).

Generally, ambidextrous innovation may have both positive and negative impacts on firm performance. On the one hand, the duality of ambidextrous innovation implies that instead of engaging in either exploratory or exploitative innovation activities, pursuing both concurrently is a better way to spur performance [33]. The logic behind this argument is that these two types of innovation activities reinforce each other due to their complementary effects [34]. For instance, increasing proficiency and efficiency arising from exploitative innovation help firms develop new capabilities for exploratory innovation [67]. In turn, the breakthrough innovations in exploration not only offer refinement orientations for exploitative innovation [68], but also improve the economics of current exploitative efforts [67].

In addition, these synergistic effects could be amplified through the specialized and intermediated characteristics of the cluster [28]. That is, to promote performance, firms embedded in a networking cluster can largely specialize and outsource exploration or exploitative innovation activities to other firms [69]. In this process, an optimized structure of cluster governance also enables firms to become ambidextrous by fostering knowledge transfer and resource exchange [55].

On the other hand, exploration and exploitative innovations require enormously different knowledge domains and technological learning routines [23]. These two innovations, therefore, are fundamentally incompatible especially when firms face resource-allocation constraints [37]. In other words, resource exclusivity exists between exploration and exploitative innovations and creates competing effects between the two innovations [68]. Firms thus should split scarce organizational resources between the two types of innovations [33,67]. Such competitive tension may increase co-ordinational and transitional costs, negatively impacting firm performance [68].

2.3. Network Embeddedness and Firm Performance in Clusters

Introduced by Granovetter [57], the concept of network embeddedness has been adopted widely in organizational research to reveal how a firm's embeddedness in an inter-organizational network matters for its economic behaviors and innovation activities [70]. The theory of network embeddedness suggests that a network consists of many participants who interact with each other, and their interdependent activities are impacted not by a single participant, but by multiple participants through various social relationships. Hence, social relations like exchange and collaboration among actors could deeply influence innovation processes and organizational outcomes [71].

To date, the literature on the interorganizational network has identified three main types of network embeddedness, including relational, structural, and positional embeddednesses, and distinguished their roles in stimulating firm performance. Relational embeddedness reflects the quality and strength of direct ties between two firms [72]. Direct connections foster information and resource exchange among network members. Hence, relational embeddedness helps cluster firms improve their performance by strengthening closeness in the relationship among actors in a network.

Second, structural embeddedness emphasizes the role of common ties stemming from the existence of common partners between two firms. It engenders deterrence-based trust among firms and thus, brings social monitoring benefits of structural embeddedness to firms, especially when they face collaboration problems [72].

Lastly, positional embeddedness relates to the centrality of an organization's position in a network [73]. If a firm takes a central position in the network, it can enjoy both information availability and reputational benefits, more easily obtain various resources required for innovation [74], and reduce informational constraints in the process of partner search and collaboration [72]. This, therefore, strengthens mutual trust among partners and mitigates opportunism, particularly in the context of clusters [75].

Meanwhile, some scholars in the field of regional innovation systems have extended the idea of network embeddedness by considering different processes of knowledge creation behind spatial clustering [76]. Particularly, they distinguish between the knowledge creation process within and across clusters. The former process emphasizes the value of local buzz, a concept that refers to "the network of information and communication linkages which develop within a cluster" [76] (p. 38), in interactive processes of localized learning. These local linkages and interactions in a cluster, called local embeddedness, facilitate local knowledge transfer and improve knowledge appropriation [77].

The process of inter-cluster knowledge creation captures the role of global pipelines in strengthening extra-local knowledge flows across clusters [76]. The pipelines imply that firms are embedded in a global innovation network rather than only located in a local innovation network [78]. They thus reflect the communication channels stemming from non-local embeddedness for distant interactions. These channels are essential for non-incremental knowledge exchange between different clusters [76]. Current studies have found strong evidence to confirm these positive effects of global pipelines in several industrial clusters (e.g., [78]). Furthermore, local buzz and global pipelines mutually reinforce the knowledge flows within and across clusters [79]. Therefore, they complement the dynamic process of creating interactive learning.

Taken together, network embeddedness stimulates firm performance mainly through the mechanisms of knowledge access and resource mobilization [80]. However, network embeddedness may also have contrasting effects on organizational outcomes in the cluster. Excessive network embeddedness leads to redundant direct and indirect ties that accelerate the learning speed in the collaboration network [41], as well as engendering network inertia inhibiting network change [81]. Under both situations, overwhelming network embeddedness restricts a firm's ability to generate diverse ideas and thus, hinders its performance in the collaboration network [41]. In addition, central firms face limits to the reduced prestige benefits and alliance value of connection with other highly embedded firms in similar network positions [42].

2.4. A Configurational Analysis of Conjunction Effects

To sustain a competitive advantage, firms must implement an ambidextrous innovation strategy [35]. This indicates that firms should build collaborative interorganizational networks for accomplishing this goal [82]. Generally, interorganizational interdependence and network embeddedness have joint effects since they are the two main mechanisms driving the emergence and dynamic evolution of inter-organizational networks [73]. The social structure of interorganizational interdependence (especially resource interdependence) captures the exogenous mechanism of network formation [61]. To deal with the exogenous interdependencies, firms seek cooperation and thus, connect with others who have the resources and capabilities they need [73]. By contrast, network embeddedness reflects the endogenous network-formation mechanisms that help firms search for appropriate partners for collaborative innovation in clusters [83].

Furthermore, network embeddedness may affect two dimensions of interorganizational interdependence: mutual dependence and power imbalance [84]. As mentioned above, network embeddedness, especially relational and structural embeddedness, promotes mutual dependence among firms through the formation of intra- and inter-cluster linkages. On the flip side, positional embeddedness may induce the positional imbalance between a peripheral and a central firm, which therefore engenders a power imbalance between those firms [72].

Finally, resource-allocation constraints for innovation lead firms to face the inherent trade-offs between exploratory and exploitative orientations [68,82]. Firms thus may "outsource" these explorative or exploitative activities to other firms in clusters [29] and seek appropriate exploratory or exploitative partners for different types of collaborative activities [85]. In both situations, network embeddedness helps cluster firms determine whom to partner with [73].

In summary, the interactions among interorganizational interdependence, network embeddedness, and ambidextrous innovation result in conjunction effects on firm performance in clusters. Such effects reflect the characteristics of causal complexity in the regional innovation system [9]. Hence, we need to adopt a new methodology to deeply explore the combined effects of multiple explanatory factors [47]. To integrate these conjunction effects, we introduce the fsQCA method to build a theoretical research framework for examining the multiple alternative paths to promote firm performance in clusters.

3. Methodology

3.1. Sample and Data Collection

We conducted a questionnaire survey to collect data from a list of cluster firms in five high-tech industrial parks in Shanghai, a new world-leading innovation hub. The questionnaire we designed includes two parts. The first part refers to firms' basic information, such as firm size, age, ownership, and the sector of SEIs. Specifically, we focus on seven sectors in SEIs classified by the National Development and Reform Commission (NDRC) of China. These sectors include next-generation information technology (IT), high-end equipment manufacturing, new materials, biotechnology, new-energy vehicles (NEVs), new energy, and energy-efficient and environmental technologies. The second part includes 40 items related to collaborative innovation activities in clusters. We sent questionnaires widely to senior and middle managers who have a solid understanding of such activities within their firms. The data-collection period was from June 2019 to September 2019. A total of 340 questionnaires were distributed and 292 valid questionnaires from 292 firms were finally received to form our sample, with a valid response rate of 85.9%.

Table 1 shows the characteristics of the sample. In terms of firm age, about 64% were young firms with less than 5 years of experience in the industry. Regarding ownership, almost half of the sample were private enterprises (PEs). The second-ranked ownership is state-owned enterprises (SOEs), accounting for 18.2%. About the industry sector, 30.8% of the firms were in the IT industry, 19.5% were in the energy-efficient and environmental technologies industry, 15.1% were in the biotechnology industry, and 10.6% were in the NEVs industry. Lastly, in terms of firm size, only 12.3% were firms with more than 300 employees. In other words, firms in SEIs are mainly small and medium-sized enterprises, so they should develop collaborative relationships in clusters to conduct innovation.

Table 1. Characteristics of the sample.

Variables		Percentage (%)
Firm size (Number of employees)	<10	13
	11–50	33.6
	51–100	21.6
	101–300	19.5
	>300	12.3
Firm age (years)	<3	30.5
	3–5	33.6
	6–10	14.7
	11–15	14.7
	>15	6.5
Firm ownership	State-owned Enterprises	18.2
	Private Enterprises	47.9
	Foreign Invested Enterprises	14.7
	Sino–Foreign Joint Ventures	10.3
	Others	8.9
Industry sector	Energy efficient and environmental technologies	19.5
	Next-generation information technology (IT)	30.8
	Biotechnology	15.1
	New energy	10.6
	New-energy vehicles (NEVs)	9.2
	High-end equipment manufacturing	6.9
	New materials	7.9

3.2. Measurement

We draw on previous studies to ensure the validity of the measurements. All the items (see the details in Appendix A Table A1) in the second part of the questionnaire are measured by a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Following the measurement method used in [86], we used the average scores of items for each construct because all constructs in our research were multi-item measurements. To ensure the questionnaire quality, we also implement a pretest before release.

3.2.1. Interorganizational Interdependence

Integrating the perspective of resource dependence theory and resource-based view (e.g., [62,87]), we use resource interdependence (RI) and task interdependence (TI) to reflect interorganizational interdependence. Resource interdependence is selected because resources are necessary for firms to build sustainable competitive advantage. We use three items to measure resource interdependence by considering the value, rareness, and non-substitutability nature of resources [88,89]. We also include task interdependence that largely stems from resource exchange and joint action (e.g., joint decision-making) during collective problems solving. Particularly, resource complementarity induces the division of labor among partners, which increases task interdependence and creates coordination needs [61]. Firms thus should coordinate the division of labor between exchanges or partners [90,91]. Hence, a tight connection exists between task interdependence and coordination [92]. Building on the work of [61,93,94], we adopt three items to measure task interdependence from the perspective of coordination. The items include the extent of coordination, task decomposition, or adjustment of the division of labor between partners in the cooperation process design of innovation solutions.

3.2.2. Ambidextrous Innovation

Since ambidextrous innovation is a combination of exploration and exploitation [95], we extend its representation by integrating exploratory and exploitative innovations. Each of these two innovations was measured by four items selected from previous studies [65,96]. Specifically, the four measures of exploratory innovation (EXPR) capture the extent to which firms develop new products, services, technologies, or markets departure from existing knowledge, experience, and skills [96]. Conversely, the four measures of exploitative innovation (EXPI) capture the extent to which firms improve existing technologies, services, markets, and products using old knowledge, experience, and skills [65].

3.2.3. Network Embeddedness

In the literature, the conception of dual embeddedness (e.g., [97]) and the idea of local and non-local network ties or cluster relationships have been well accepted in the studies of cluster and regional development (e.g., [76]). Based on these observations, we classify the linkages between firms in clusters into two kinds of network embeddedness: local network embeddedness (LME) and non-local network embeddedness (NME). Drawing on the research conducted by [98–100], for each type of network embeddedness, a ten-item scale has been adopted to explore the degree of intra- or extra-cluster linkages among firms and their partners (including suppliers, customers, universities, research institutes, and science–technology intermediaries) in local and non-local network channels within and across clusters.

3.2.4. Firm Performance

Six items from past research [101–103] were integrated to measure firm performance (PERF) relative to their principal competitors. They include market share, turnover, profitability, assets growth rate, revenue growth rate, and overall reputation. Since these items indicate both financial and non-financial aspects of performance, we can effectively measure the overall firm performance.

3.3. Validity and Reliability

We carried out several reliability tests and validity tests. First, to confirm construct reliability, we used the indicators of the factor loadings, values of Cronbach's alpha, and the composite reliability (CR). Table 2 shows that our questionnaire has acceptable internal consistency reliability. The results also suggest satisfactory discriminant validity since all average variance extracted (AVE) values were above the threshold of 0.50. In addition, the seven-factor of the CFA model shows good fit statistics with $\chi2/df = 1.451$, RMSEA = 0.039, CFI = 0.975, TLI = 0.973, NFI = 0.925, and GFI = 0.858. It also indicates that our research has good discriminant validity. Altogether, these tests offer evidence that our model has strong construct and convergent validity. They also ensure the effectiveness and accuracy of the questionnaire in this study.

The descriptive statistics and correlation analysis of all variables are shown in Tables 3 and 4 respectively. They indicate that positive correlations exist between these factors in the cluster and firm performance. These results are consistent with relevant findings reported in a great deal of theoretical and empirical research (e.g., [68,104]).

Table 2. Factor Loadings, Cronbach's Alpha, CR, and AVE.

Constructs	Items	Loadings	Alpha	CR	AVE
Resource Interdependence (RI)	RI1	0.850	0.874	0.8739	0.698
	RI2	0.841			
	RI3	0.815			
Task Interdependence (TI)	TI1	0.855	0.874	0.8742	0.6985
	TI2	0.828			
	TI3	0.824			

Table 2. *Cont.*

Constructs	Items	Loadings	Alpha	CR	AVE
Local Network Embeddedness (LME)	LME1	0.824	0.961	0.961	0.7114
	LME2	0.845			
	LME3	0.856			
	LME4	0.838			
	LME5	0.871			
	LME6	0.861			
	LME7	0.834			
	LME8	0.823			
	LME9	0.844			
	LME10	0.837			
Non-Local Network Embeddedness (NME)	NME1	0.851	0.962	0.9616	0.7145
	NME2	0.85			
	NME3	0.832			
	NME4	0.832			
	NME5	0.874			
	NME6	0.821			
	NME7	0.835			
	NME8	0.852			
	NME9	0.829			
	NME10	0.875			
Exploratory Innovation (EXPR)	EXPR1	0.837	0.900	0.9004	0.6934
	EXPR2	0.853			
	EXPR3	0.803			
	EXPR4	0.837			
Exploitative Innovation (EXPI)	EXPI1	0.814	0.902	0.9027	0.6988
	EXPI2	0.844			
	EXPI3	0.824			
	EXPI4	0.861			
Firm Performance (PERF)	PERF1	0.817	0.930	0.9303	0.6899
	PERF2	0.832			
	PERF3	0.852			
	PERF4	0.825			
	PERF5	0.816			
	PERF6	0.841			

Note that loadings indicate factor loadings, Alpha indicates Cronbach's alpha, CR is the abbreviation of composite reliability, and AVE is the average variance extracted.

Table 3. The Correlation Statistics.

Variables	1	2	3	4	5	6	7
1 RI	1						
2 TI	0.889	1					
3 LME	0.906	0.922	1				
4 NME	0.920	0.924	0.961	1			
5 EXPR	0.883	0.882	0.915	0.929	1		
6 EXPI	0.901	0.874	0.926	0.932	0.887	1	
7 PERF	0.913	0.911	0.940	0.949	0.916	0.916	1

Note: All correlations are significant at $p < 0.01$.

Table 4. Sample Descriptive Statistics and calibration values.

Variables	Mean	SD	Min.	Max.	Calibration Values		
					Fully In (95th)	Crossover (50th)	Fully Out (5th)
1 RI	3.8573	1.10675	1.00	5.00	5.00	4.33	1.33
2 TI	3.8137	1.12820	1.00	5.00	5.00	4.33	1.33
3 LME	3.7870	1.08677	1.40	4.90	5.00	4.20	1.10
4 NME	3.7942	1.08761	1.20	4.80	4.60	4.30	1.50
5 EXPR	3.7671	1.08732	1.25	5.00	4.75	4.25	1.50
6 EXPI	3.7851	1.10034	1.25	5.00	5.00	4.00	1.00
7 PERF	3.8083	1.07917	1.17	5.00	4.67	4.33	1.50

3.4. Data Analysis Using fsQCA

The fsQCA method is a set-theoretic configurational method. We have three considerations to employ fsQCA to answer the driver of cluster firms' performance. They are that: (1) This method does not require a large sample set and is more suitable for processing a medium-sized sample, neither large enough to adopt quantitative approaches like traditional regression analysis nor too small to apply qualitative methods such as case study research and grounded theory [48]. (2) Rather than focusing on correlational theorizing and net effects thinking by traditional regression methods, fsQCA emphasizes configurational theorizing and combined effects thinking, which helps reveal the holistic impacts of different factors in the regional innovation systems [45]. Such a method can advance the understanding of complex nonlinear relationships among inter-organizational interdependence, ambidextrous innovation, and network embeddedness on firm performance in clusters. (3) fsQCA supports equifinality and thus, is typically suitable for integrating different research theories to develop an overarching theoretical framework [105,106]. In this regard, it is beneficial to explain how or why multiple alternative paths or combinations can produce the same outcome when complex interdependencies exist among different elements [16,45,107]. Hence, it also helps us to identify the complementarity or substitution relationships among configurational antecedents that lead to high firm performance [108].

In this study, the outcome is 'firm performance' (PERF). The antecedents we explored are several constructs related to collaborative innovation in clusters, including 'resource interdependence' (RI), 'task interdependence' (TI), 'exploratory innovation' (EXPR), 'exploitative innovation' (EXPI), 'local network embeddedness' (LME), and 'non-local network embeddedness' (NME). Since each of these constructs (also called causal conditions) in our research involved multiple items, we measured each construct using the average score of its corresponding item measures in the calibration procedure [86]. We adopted a direct approach of calibration in [50] and the software of fsQCA 2.5 to calculate set membership scores of both the causal conditions (i.e., resource interdependence) and the outcome (i.e., firm performance) by transforming the value of all variables into a fuzzy set value ranging from 0 to 1 [46]. To transform the variable values, we set three different qualitative anchors that determine the threshold for full membership, full non-membership, and the crossover point [50]. Similar to the methods used in [86,109] to form the fuzzy sets, we calculated the cutoff points for each variable at the 5th, 50th, and 95th percentiles for full membership, crossover, and full non-membership, respectively.

Table 2 summarizes the corresponding set membership scores of all variables after calibration. For instance, the outcome of interest in our research is firm performance measured by the average scores of the constructs consisting of 6 items. We chose the 50th percentile score (=4.33) of all firm performance in our data as the crossover point. Regarding the boundaries of full membership in the set of high-performing firms, if a firm's performance exceeds 4.67 (the 95th percentile), it is coded as 1. By contrast, if a firm's performance is below 1.50 (the 5th percentile), it belongs to the set of full non-membership. In addition, we added a constant of 0.001 to set membership scores of all variables after calibration to avoid theoretical problems of analyzing sets with membership scores exactly equal to 0.5. This membership setting was adopted in relevant studies [46,110].

4. Results

4.1. Necessary Conditions

After the calibration, we conducted a necessity analysis to examine whether the six causal conditions (antecedents) are necessary for promoting firm performance in clusters. In this analysis, we considered two indicators including consistency scores and coverage scores.

As reported in Table 5, the levels of these two indicators for all conditions (and their negations) are lower than the recommended threshold value of 0.9 [50]. In other words, none of these six causal conditions by itself is necessary for determining the performance of cluster firms. This result confirms the expected causal complexity in the context of clusters (e.g., [9]). It suggests that combinations of these conditions are more suitable for explaining performance outcomes than a single condition.

Table 5. Necessity of the conditions relative to high performance.

Condition	Consistency	Coverage	Condition	Consistency	Coverage
RI	0.822	0.836	NME	0.830	0.805
~RI	0.564	0.589	~NME	0.523	0.575
TI	0.786	0.834	EXPI	0.876	0.780
~TI	0.595	0.596	~EXPI	0.465	0.569
LME	0.809	0.826	EXPR	0.807	0.800
~LME	0.572	0.595	~EXPR	0.532	0.570

Note: "~" = Negation (NOT).

4.2. Sufficiency Analysis

We then performed a sufficiency analysis to disentangle combinations of these six causal conditions sufficient for the high performance of cluster firms. The key step in this analysis is to create a truth table that explains how reliably a combination of the six casual conditions results in the outcome [111]. The truth table is built based on the equation PERF = f(RI, TI, LME, NME, EXPR, EXPI). Rather than considering all logically possible combinations, we simplify the truth table by using frequency and consistency thresholds [46,50].

We set the frequency threshold (also called the minimum acceptable number of cases) to 4. In other words, all combinations with fewer than four cases are excluded from further analysis. Therefore, there are 238 remaining cases, accounting for 81.5% (=238/292) of the sample. This proportion complies with the criterion used in fsQCA research [112], which is to include at least 75% of the sample after removing configurations with low frequency in the truth table.

Following the tradition in the QCA literature (e.g., [50,112]), we used two indicators of consistency, named raw consistency and PRI consistency, to exclude the less significant configurations. In parameter settings, we used the raw consistency threshold of 0.8 suggested in relevant studies (e.g., [113,114]). This threshold is a general setting when adopting the

QCA approach to large-N (N > 50) settings [115]. Additionally, we used a cutoff of 0.75 for PRI consistency. This value was also used by [106,116].

On the other hand, we rely on both types of consistency to determine whether each row (i.e., combinations of conditions) in the truth table indicates high performance. Particularly, only combinations with a raw consistency $\geq$0.8 and a PRI consistency $\geq$0.75 are considered a reliable set of causal conditions for achieving high performance [106]. Furthermore, we used the algorithm of counterfactual analysis in fsQCA software to minimize combinations of causal conditions that lead to high-performance outcomes [117]. The final step is to proceed with a standard analysis to identify three types of solutions: the complex solution, the parsimonious solution, and the intermediate solution. Following the tradition in the literature on fsQCA [46,50], we explain the causal configurations of high performance based on the intermediate and parsimonious solutions that can be used to distinguish the core and peripheral casual conditions.

The intermediate solutions are shown in Table 6, containing six solutions or configurations for high performance. Since the consistency level of each configuration is greater than 0.9, it indicates a high level of overall solution consistency (=0.901). In terms of overall solution coverage, the combined models could explain almost 78.7% of cases with high performance. Especially, configuration 1 with the highest raw coverage provides the combination of conditions that best explain the driver of firm performance in clusters. In addition, all six configurations include EXPI. It indicates that exploitative innovation plays a vital role as a core casual condition and becomes the main driver for high-performance outcomes.

Table 6. Configurations for high performance.

Outcome: Firm Performance						
Condition	**Configurations**					
	1	2	3	4	5	6
RI		•	•	•		
TI	•	•			•	
LME	•		•			•
NME	⊗	•	•		•	•
EXPI	●	●	●	●	●	●
EXPR				•	•	•
Consistency	0.965	0.963	0.959	0.946	0.960	0.957
Raw coverage	0.477	0.680	0.698	0.710	0.668	0.685
Unique coverage	0.009	0.008	0.015	0.029	0.001	0.007
Overall solution coverage	0.787					
Overall solution consistency	0.901					

Note: "●" = core condition (present); "⊗" = peripheral condition (absent); "•" = peripheral condition (present); blank space = the causal conditions may be present or absent.

Configuration 1 (C1) indicates that the performance of cluster firms can improve when the following conditions are contemporaneously present: task interdependence, local network embeddedness, exploitative innovation, and the absence of non-local network embeddedness. In this configuration, cluster firms should create close cooperation with other partners in the local cluster and implement exploitation-centered innovation for high performance. This demonstrates that if tasks are highly interdependent, intra-cluster linkages are crucial for heightened performance.

Configuration 2 (C2) shows a combination of factors, including resource interdependence, task interdependence, non-local network embeddedness, and exploitative innovation, where the former three factors are peripheral conditions. The blank space in this configuration also suggests that local network embeddedness plays a minor role. Therefore, when resources and tasks are highly interdependent, non-local network embeddedness helps provide diverse information and knowledge to enhance exploitative innovation and thus, improve overall performance.

Like configuration 2, configuration 3 (C3) suggests that when resources are highly interdependent, cluster firms can improve their performance by adopting a dual-network embeddedness strategy and concentrating on exploitative innovation.

Configuration 4 (C4) combines task interdependence, exploitative innovation, and exploratory innovation. Again, exploitative innovation is a core condition, while task interdependence and exploratory innovation are peripheral conditions. This configuration implies that when firms face high task interdependence among partners, a high level of ambidextrous innovation enables firms to become high performers.

Configuration 5 (C5) provides another pathway to achieve high performance in the condition of high task interdependence. That is, to strengthen non-local network embeddedness, firms can leverage the synergistic effects of exploitation and exploration.

Finally, configuration 6 (C6) shows that a high level of ambidextrous innovation combined with a high degree of dual network embeddedness can contribute to high performance regardless of interorganizational interdependence. This finding reveals their complementary roles in promoting performance in configuration 6.

4.3. Robustness Test

To evaluate the robustness of our methodology, we performed a predictive validity test, robustness analysis of the fsQCA results, and comparisons with related methods.

The predictive validity test offers insights into "how well the model predicts the dependent variable in additional samples" [117] (p. 15). This test is important since a model that fits our sample well does not necessarily mean that it can make a good prediction. To perform predictive validity testing, we randomly split our sample into two equal-size subsample sets. Each subsample set includes 146 firms. These two subsamples can be seen as the analysis group (Group 1) and holdout group (Group 2), respectively. After running the fsQCA and obtaining the highly consistent solutions using sample data in Group 1, we investigated the predictive power of these solutions on the Group 2 data by checking whether the consistency of these solutions is still greater than the suggested threshold of 0.8. As reported in Table 7, the overall solution consistency for both groups is 0.917 and 0.969, respectively, indicating good predictive validity. Then, we repeated this procedure, using sample data from Group 2 to obtain solutions and using sample data from Group 1 to test the predictive power of the solutions. Although we do not report the results in this article, the overall solution consistency is still higher than the recommended threshold.

Table 7. Intermediate solution of predictive validity test.

Outcome: Firm Performance Model: PERF = *f*(RI, TI, LME, NME, EXPR, EXPI)				
Configurations (Based on Data from Group 1)	**Group 1**		**Group 2**	
	Raw Coverage	**Consistency**	**Raw Coverage**	**Consistency**
1. RI * TI * NME * EXPI	0.701	0.956	0.657	0.972
2. RI * LME * NME * EXPI	0.720	0.951	0.676	0.968
3. RI * TI * EXPI * EXPR	0.684	0.981	0.644	0.969
4. RI * LME * EXPI * EXPR	0.686	0.961	0.654	0.970
5. RI * NME * EXPI * EXPR	0.703	0.963	0.671	0.964
6. TI * LME * NME * EXPI * EXPR	0.669	0.974	0.640	0.972
Overall Solution coverage	0.794		0.678	
Overall Solution consistency	0.917		0.969	

Note: "*" = Logical conjunction (AND).

We also tested the robustness of the fsQCA results under various settings of the consistency cutoff and frequency threshold. First, we replicated the fsQCA procedure by changing the consistency cutoff from 0.8 to 0.85. As shown in Table 8, the consistency of each configuration and the overall solution consistency are both greater than 0.9. When the case frequency threshold was adjusted from 4 to 5, it was found that using the obtained configurations kept high performance. Both robustness tests indicate that our findings are relatively stable.

Table 8. Intermediate solution of robustness test by changing consistency cutoff.

Outcome: Firm Performance			
Model: PERF = *f*(RI, TI, LME, NME, EXPR, EXPI)			
Case Frequency Threshold: 4			
Consistency Thresholds: 0.85			
Configurations:	**Raw Coverage**	**Unique Coverage**	**Consistency**
RI * EXPI * EXPR	0.71	0.03	0.947
TI * LME *~NME * EXPI	0.477	0.009	0.965
RI * TI * NME * EXPI	0.68	0.022	0.964
TI * NME * EXPI * EXPR	0.669	0.001	0.961
LME * NME * EXPI * EXPR	0.685	0.008	0.957
LME * NME * LYCX * EXPR	0.685	0.008	0.957
Overall Solution coverage:		0.772	
Overall Solution consistency:		0.906	

Note: "*" = Logical conjunction (AND), "~" = Negation (NOT).

Following the roadmap of [46], we compared our results with those of similar models and investigated whether the results produced by different methods could support each other. For this purpose, the results of our fsQCA were compared with the results of a traditional method, such as path analysis. When using path analysis, the structural equation model (SEM) is often recommended when a study involves complex models [118]. We therefore established an empirical research framework by implementing the SEM which considers the mediating role of ambidextrous innovation in the relationship between network embeddedness and firms' performance. This model was tested by using the AMOS modeling software (Version 22).

The results of the analysis using SEM (shown in Table 9) hint at several findings consistent with our results. First, local network embeddedness and non-local network embeddedness have a positive impact on cluster firm performance, which can support the relationship between configurations C1, C2, C3, C5, C6, and firm performance. Second, non-local network embeddedness has a significant positive impact on exploratory and exploitative innovation. This indicates that there is an interaction between non-local network embeddedness and ambidextrous innovation. It also validates the relationship that exists between configurations C2, C3, C5, C6, and firm performance. Third, local network embeddedness has no significant effect on exploratory and exploitative innovation. This to some extent reveals why non-local network embeddedness can lead to high performance (see configurations C2 and C4). Fourth, the mediation effect of ambidextrous innovation on the relationship between network embeddedness and firm performance is not very significant. This indicates that the joint influence mechanism of network embeddedness and ambidextrous innovation on firm performance is not mainly through the mediation effects mentioned above. In this regard, our findings fairly complete the findings from SEM and reveal the role played by the effects of causal complexity in the above-mentioned process.

Table 9. Path coefficients from SEM.

Path from	To	Path Coefficient	p-Value
Local Network Embeddedness (LME)	Firm Performance (PERF)	0.047	0.001 **
Non-Local Network Embeddedness (NME)	Firm Performance (PERF)	0.940	0.000 **
Exploratory Innovation (EXPR)	Firm Performance (PERF)	0.231	0.002 **
Exploitative Innovation (EXPI)	Firm Performance (PERF)	0.052	0.057
Local Network Embeddedness (LME)	Exploratory Innovation (EXPR)	0.095	0.341
Local Network Embeddedness (LME)	Exploitative Innovation (EXPI)	0.60	0.062
Non-Local Network Embeddedness (NME)	Exploratory Innovation (EXPR)	0.767	0.000 **
Non-Local Network Embeddedness (NME)	Exploitative Innovation (EXPI)	0.659	0.000 **

Note: ** p-value < 0.01.

5. Discussion

5.1. Main Conclusions

By conducting a fsQCA analysis of questionnaire data from 292 cluster firms in Chinese strategic emerging industries, this paper explores how the combined effects of interorganizational interdependence, network embeddedness, and ambidextrous innovation drive firm performance. In summary, two main findings are as follows:

(1) Clusters, as one of the factors in regional innovation systems, have complex causal relationships with firm performance. A single condition by itself will not lead to high firm performance. Instead, spurring the performance of cluster firms mainly depends on the holistic or conjunction effects of these factors in the regional innovation system.

(2) Exploitative innovation plays a core condition to achieve high firm performance in all six different configurations. In other words, due to the equifinality characteristic of causal complexity, a firm in the cluster has multiple alternative ways to improve performance. However, to become a high performer, it must rely on exploitative innovation and different factors from interorganizational interdependence and network embeddedness in various contingencies. By contrast, exploratory innovation alone is unlikely to stimulate performance.

Further, we identify two main pathways for the regional innovation system to stimulate firm performance in the context of clusters.

Performance enhancement path 1 is based on specialization, especially in exploitative innovation (C1–C3). In this type of pathway, network embeddedness is a necessary condition, while the conjunction effects of different types of network embeddedness and exploitative innovation on firm performance are closely related to the typical dimensions of inter-organizational interdependence. Specifically, in the absence of non-local network embeddedness as the peripheral causal condition, local network embeddedness and exploitative innovation can only be complementary to upgrading firm performance when tasks are highly interdependent (see C1).

Meanwhile, there is a trade-off between local and non-local network embeddedness in this path. Path 1 further suggests that when both task interdependence and exploitative innovation are high, local network embeddedness should be chosen to promote firm performance. Conversely, if only a high degree of resource interdependence exists, local network embeddedness and task interdependence can act as substitutes in the performance enhancement process (compare C2 and C3).

Performance improvement path 2 is based on ambidexterity, especially ambidextrous innovation (C4–C6). This type of path emphasizes the conjunction effects of two peripheral causal conditions: exploratory innovation and non-local network embeddedness. Further, when firms face a high resource interdependence, they can boost performance by conducting ambidextrous innovation, even without a high level of network embeddedness (see C4). Comparing C4 and C5, we can conclude that the type of interorganizational dependence a firm faces directly determines whether the high level of non-local network embeddedness contributes to high performance. Finally, when a high level of non-local network embeddedness exists, exploratory innovation and resource interdependence can substitute for each other in promoting performance (compare C2 and C5 or C3 and C6).

Based on the above, we assert the following two propositions:

Proposition 1. *The combination of interorganizational dependence, network embeddedness, and ambidextrous innovation is essential for driving the performance of cluster firms. Particularly, exploitative innovation is a core condition to generate high performance.*

Proposition 2. *The improved performance of cluster firms is caused by the appropriate two pathways based on the six configurations.*

5.2. Theoretical Contributions

In this paper, we build an integrative research framework by combining three main research theories: resource dependence, social network, and ambidexterity. By introducing the QCA approach into cluster innovation research, we can develop this framework to explore the holistic effect of several key cluster factors in the regional innovation system that led to high levels of firm performance. Previous empirical studies focused on the net effects of individual factors on cluster firms' performance (e.g., [23]). They ignored how combined effects of multiple factors (i.e., causal recipe) can contribute to firm performance in clusters [45]. Our multi-theoretical model fills this research gap though capturing the characteristics of conjunction and equifinality in the complex process of collaborative innovation in industrial clusters.

More specifically, in our study, the combination of inter-organizational dependence, network embeddedness, and ambidextrous innovation could enhance the performance of cluster firms via different equifinal configurations that lead to the same outcome. In the configurations for promoting performance, these factors above may operate as either complements or as substitutes due to different causal recipes. Such findings not only deepen the cluster innovation research by following the combinatorial logic and adopting a holistic perspective [106,111] but also respond to recent calls to deepen research in resource dependence theory and cluster innovation capabilities by integrating multiple theoretical perspectives [119] and examining the impact of local and global knowledge networks on business performance, respectively [21]. Our configurational analysis suggests that conditions that play important roles in one configuration may become less important in another. This gives new insights into the confusion about whether firms' performance in clusters is driven by intra- or extra-cluster linkages [76], or specialized in exploitation or exploration [28,29].

In addition, according to our analysis, the configuration view also helps clarify the coupling mechanism of these cluster factors in the regional innovation system to raise firm performance synergistically. Specifically, it uncovers that the pathway to high performance is not determined by a single factor effect but by nonlinear and complex effects of multiple factors combined. Following the guideline of [114], Table 10 summarizes the findings of relevant studies and our study, respectively. The relevant studies on clusters have identified interorganizational dependence, ambidextrous innovation, and network embeddedness as necessary conditions for achieving high performance [6,29,120,121]. However, through the causal complexity analysis, our study implies that no single strategy is necessary for promoting the performance of cluster firms. This conclusion means that cluster firms can achieve high performance by flexibly choosing different strategic combinations in a complex and dynamic external environment, without having to "do everything". For example, when a firm faces capacity constraints and cannot implement an ambidexterity strategy or dual-network embeddedness, the firm can focus on exploitative innovation and rely on local or non-local networks to obtain resources that match its capabilities, thereby improving its performance.

Table 10. Summary of findings from our research and related studies.

		Related Studies	Our Study
Perspective		The findings are mainly about the effect of single or dual strategies in different contexts	The findings are about the combinations of cluster factors that likely lead to high performance
Performance enhancement strategies in clusters	Interorganizational Interdependence (II)	• On average, II is positively related to the performance of cluster firms [61,122]. • II enhances the performance of cluster firms by increasing NE [60].	• No single strategy (II, AI, or NE) is necessary for the high performance of cluster firms. • High II combined with high AI can yield high performance (C4). • High II combined with high NE can yield high performance when the level of exploitative innovation is high (C3).
	Ambidextrous Innovation (AI)	• AI has positive impacts on cluster firms' performance by leveraging the synergistic effects of exploration and exploitative innovation [28,55]. • AI is negatively related to the performance of cluster firms due to resource exclusivity that exists between exploration and exploitative innovation [33,67]. • II may hinder the effectiveness of AI in improving firm performance [32].	• While AI can promote cluster firms' performance (C4–C6), only a high level of exploitative innovation can also enhance performance via different pathways (C1–C3). • Exploitative innovation plays a core condition to achieve high firm performance (C1–C6).
	Network Embeddedness (NE)	• Generally, NE enhances cluster firms' performance [40,120,123]. • NE can produce higher performance through the mediating effect of AI [124].	• Local and non-local NE can promote cluster firms' performance via different pathways (C1, C5). They can also operate as complements in the performance enhancement process (C3, C6). • High NE combined with high AI can yield high performance (C6).

Furthermore, previous studies have shown that both ambidextrous innovation and network embeddedness have contradictory effects on firms' performance [26,68]. In this study, we pose a new perspective on these inconsistent findings by considering the cluster context and deeply exploring how different dimensions of these factors as interacting parts of the whole contribute to high performance. Our study offers a systemic explanation for drivers of cluster firms' performance by considering configurations of these factors rather than considering individual factors in isolation. Firstly, in the context of open innovation, firms that outsource exploratory innovation and focus on exploitative innovation may perform better than firms that implement ambidextrous innovation. This study points out that there are three configurations focusing on exploitative innovation that can achieve high performance. This provides a new explanation for companies such as Cisco that still have strong competitiveness without implementing the ambidextrous innovation strategy [28]. Secondly, our analysis shows how resource interdependence hinders the effectiveness of ambidexterity in improving firm performance from a configuration view. This is because resource interdependence and ambidextrous innovation have complementary effects in the process of promoting corporate performance (see C3). When a low level of resource interdependence cannot be matched with a high level of ambidextrous innovation, firms may not be able to achieve high performance. Thirdly, our findings support the conventional viewpoint that network embeddedness improves cluster firm performance. Further, our study identifies how to achieve high performance in three different network-embedded modes: local network embeddedness or non-local network embeddedness, or dual-network embeddedness. These efforts could help identify potential boundary conditions for exploiting dual-network embeddedness to promote the performance of cluster firms when they specialize in exploitation or when they pursue exploitation and exploration simultaneously.

5.3. Managerial Implications

This study has some managerial implications for cluster management in SEIs as well as performance improvement of cluster firms. On the one hand, existing literature on cluster innovation has overemphasized the importance of using collaborative network resources for exploratory innovation [28,125]. It to some extent has neglected the significance of exploitative innovation for achieving high performance. The scope of exploitative innovation in the context of inter-organization relationships is not only limited to the traditional field of product innovation (e.g., the improvement of existing products), but is also related to activities such as commercialization and marketing the downstream [126]. This paper reveals that exploitative innovation is a core condition for improving firm performance in the cluster. Therefore, to strengthen firm performance, cluster firms should prioritize exploitative innovation and leverage cluster networking capacity. For example, firms can attract new customers by cultivating customer relationships [127] or creating new markets for their existing products [128]. From the perspective of the value chain, firms can also make full use of the cluster network by forming knowledge-leveraging alliances or combining complementary partner capabilities and assets to expand the breadth and depth of exploitative innovation [129]. Drawing on our findings, if the degree of resource interdependence among partners is high, firms should exploit local network embeddedness and task interdependence as alternative conditions to improve performance.

On the other hand, our work also provides another path for firms to improve their performance by pursuing ambidextrous innovation. In this regard, firms should be aware that high levels of non-local network embeddedness are the key to improving performance. Hence, to achieve better non-local network embeddedness, firms in clusters can build up extra-cluster linkages across geographic and industrial boundaries [130,131]. To further reinforce such positive impacts on performance, firms can strengthen their cooperative relationships and coordination among different partners in clusters (see configuration 5). In addition, accompanied by dual network embeddedness, firms can pursue ambidextrous innovation to accelerate performance (see configuration 6).

5.4. Limitations and Future Research

In our study, we have reported encouraging outcomes of configurational analysis on the relationship between clusters and firm performance. Future research could enrich our study in several ways. First, the questionnaires in our study were only collected in Chinese strategic emerging industries. Since different contexts and other sample data may lead to different results [132], we can further explore the research issue in this study by using data from other emerging economies or industries. When applying our questionnaire to industrial clusters in other regions, we may need to modify the measures to reflect local conditions to obtain more reliable results.

For example, most of the cluster firms in Silicon Valley are international companies and they often work closely with institutions across regions. In this context, regarding network embeddedness, local ties with entrepreneurs, service providers, and venture capital investors, as well as global linkages (e.g., durable bonds or covalent bonds) with companies and institutions in these remote clusters [133] should also be included. In addition, instead of adopting an ambidexterity strategy, some firms in Silicon Valley may implement a specialization strategy by focusing on exploitation and outsourcing exploration [28]. When switching to European clusters, the measurement of network embeddedness may be complicated, as cluster firms prefer to form tripartite partnerships between universities, research centers, and firms [1]. In this situation, the characteristics of local and non-local innovation networks associated with multinational corporation (MNC) subsidiaries in European industrial clusters [99] can be added to our framework. Furthermore, we can deepen the understanding of network embeddedness by distinguishing between horizontal and vertical linkages and by introducing cluster breadth and depth which are essential in European industrial clusters [134].

Second, the combined effects of different factors on cluster firms' performance may drift over time. We can further investigate these effects using the TQCA method based on time-series analysis [135]. Finally, in this study, we ignore some contingency factors that may influence firm performance in clusters. This limits the identification of specific configurations for promoting performance under different contextual conditions. In the future, we can follow a good example of [111] and conduct a more systematic QCA analysis by considering external environment factors (e.g., the competitive environment) and organizational factors (e.g., firm size and age).

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Appendix A

Table A1. Item description in construct measurements.

Constructs	Items	Item Description	Reference
Resource Interdependence (RI)	RI1	Acquiring rare resources from partners in the cluster	[88,89]
	RI2	Acquiring valuable resources from partners in the cluster	
	RI3	Acquiring nonsubstitutable resources from partners in the cluster	
Task Interdependence (TI)	TI1	There is a lot of coordination in the cooperation process	[60,93,94]
	TI2	There is a lot of task decomposition between partners in the cooperation process	
	TI3	There is a lot of frequent adjustment of the division of labor between partners in the cooperation process	
Local Network Embeddedness (LME)	LME1	Close communication with local suppliers	[98–100]
	LME2	Close communication with local customers	
	LME3	Close communication with local peer companies	
	LME4	Close communication with local universities and research institutions	
	LME5	Close communication with local science-technology intermediaries	
	LME6	Long-term cooperation with local suppliers	
	LME7	Long-term cooperation with local customers	
	LME8	Long-term cooperation with local peer companies	
	LME9	Long-term cooperation with local universities and research institutions	
	LME10	Long-term cooperation with local science-technology intermediaries	

Table A1. *Cont.*

Non-Local Network Embeddedness (NME)	NME1	Close communication with non-local suppliers	
	NME2	Close communication with non-local customers	
	NME3	Close communication with non-local peer companies	
	NME4	Close communication with non-local universities and research institutions	
	NME5	Close communication with non-local science-technology intermediaries	
	NME6	Long-term cooperation with non-local suppliers	
	NME7	Long-term cooperation with non-local customers	
	NME8	Long-term cooperation with non-local peer companies	
	NME9	Long-term cooperation with non-local universities and research institutions	
	NME10	Long-term cooperation with non-local science-technology intermediaries	
Exploratory Innovation (EXPR)	EXPR1	We frequently utilize new opportunities in new markets	[65,96]
	EXPR2	We experiment with new business strategies in an existing market	
	EXPR3	We utilize immature technology	
	EXPR4	We invent new products and services	
Exploitative Innovation (EXPI)	EXPI1	We regularly improve existing technology for products and services	
	EXPI2	We regularly implement small adaptations to existing products and services	
	EXPI3	We introduce improved, but existing technologies for product feature extension	
	EXPI4	We improve our provision's efficiency of products and services	
Firm Performance (PERF)	PERF1	Relative to your principal competitors, rate your firm performance on market share	[101–103]
	PERF2	Relative to your principal competitors, rate your firm performance on turnover	
	PERF3	Relative to your principal competitors, rate your firm performance on profitability	
	PERF4	Relative to your principal competitors, rate your firm performance on assets growth rate	
	PERF5	Relative to your principal competitors, rate your firm performance on revenue growth rate	
	PERF6	Relative to your principal competitors, rate your firm performance on the firm's overall reputation	

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