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Research article

Partners' centrality in scientific collaboration and exploratory innovation: Roles of patent stock and structural holes

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ABSTRACT

Studies adopting a first-order social-capital perspective have found that firms' innovation is influenced by network embeddedness in scientific collaboration. The present study adopts a second-order social-capital perspective to examine the effect of partners' centrality on exploratory innovation. We further investigate the boundaries of this effect via patent stock and structural holes (SHs), individually and jointly. Our theoretical framework is validated using negative binomial regression models and a sample of patents and joint publications by 194 Chinese pharmaceutical firms between 2007 and 2021. The results indicate that a focal firm's exploratory innovation is boosted by partners' centrality in scientific collaboration, but this effect is weakened by patent stock and SHs. Moreover, patent stock and SHs jointly influence this relationship—that is, partners' centrality has a strong positive effect on exploratory innovation when the firm holds low patent stock and occupies fewer SHs. This study offers insights into how businesses might profit from the innovation advantages of influential partners by exploring the contingencies of patent stock and SHs. Extending the framework to second-order aspects, we further illuminate the scope of the scientific collaboration–innovation issue.

1. Introduction

Exploratory innovation, which refers to organizations searching for or discovering new knowledge [1–3], is vital for firms' enduring prosperity. To accomplish the goal of exploration, many firms in science-based industries are initiating multiple scientific collaboration partnerships [4]. This is because sophisticated inventions often rely heavily on scientific knowledge [5], which is mostly produced in universities and research institutions [6]. Science-based firms such as pharmaceutical firms actively engage in publishing for various reasons, such as accessing outside resources and knowledge, attracting and retaining researchers, improving the firm's intellectual property strategies, supporting commercialization strategies, and enhancing the firm's reputation [7]. A major way to achieve this is through copublication. Thus, building a well-developed scientific collaboration network has become a crucial part of firms' exploratory innovation strategies.

Many studies have examined the effect of network embeddedness in scientific collaboration on firms' innovation from a first-order social-capital perspective [4,8,9], assuming that partners' social capital is homogeneous. Several factors can increase a firm's likelihood of improving its innovation performance, such as the number of individual-level collaborative interactions between researchers

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employed by the firm and those with academic affiliations [8], direct connections with universities, the number of academic partners collaborating indirectly [9], network breadth and strength [4], and structural holes (SHs) [10] at the organizational level. Moreover, an inverted U-shaped pattern has been identified in the relationship between the degree centrality of pharmaceutical firms and their technological innovation [10]. Studies have also examined moderating factors, including technological and market dynamics [4], patent stock, collaboration strength [10], and scientific absorptive capacity [11]. In scientific collaboration, focal firms are influenced by both first-order and second-order social capital [12]. In particular, second-order social capital has been shown to play a crucial role in influencing the performance of focal actors in various networks, such as technology alliances [13,14], a firm's board-interlock network [15], and employees' social networks [16]. Karamanos [13], for example, found that the centrality of a focal firm's technology alliance partners is conducive to its exploratory innovation. Wang et al. found that the relationship between partners' centrality diversity and the focal firm's exploratory innovation has an inverted U shape [14]. Jiang et al. [15] showed that the diversity of partners' centrality in a firm's board-interlock network has a positive correlation with innovation performance. Hirst et al. [16] suggested that individual creativity is supported by indirect network efficiency in the employees' social networks. The core assumption of these studies is that the social capital of partners varies. Indeed, in a scientific collaboration network, some partners are in central positions, while others are on the periphery. Different network positions mean different levels of social capital as well as different spillover effects of partners' social capital on the focal firm. Thus, a question arises: Does the centrality of partners in scientific collaboration benefit the focal firm's exploratory innovation, and what are the boundaries of this effect?

We investigate this question by empirically examining the effect of partners' centrality in scientific collaboration on the focal firm's exploratory innovation. Drawing on Karamanos [13] and Jiang et al. [15], we conceptualize partners' centrality as partners' ego–network degree centrality—that is, the average number of direct connections among a focal firm's partners in a given five-year window. Higher network centrality means greater positional advantage and influence in the network [17]. Partners with higher centrality send legitimacy signals, bring high-quality resources, and enhance the focal firm's visibility in the collaboration network [13], which can benefit exploratory innovation. According to the resource-based view, resources are the foundation of a firm's competitive advantage [18]. Differences in the resources firms possess form technological differences in an industry; however, differentiated resources also limit the scope and boundaries of the technological fields firms can explore. Following this logic, the effect of partners' centrality on exploratory innovation might be influenced by differences in firms' resources. Thus, we introduce patent stock and SHs as moderators to further explore the influence boundary of partners' centrality in scientific collaboration on exploratory innovation. Patent stock is an important internal technical resource, while SHs are links to key external network resources. Occupying SHs in a network means that a focal firm is exposed to abundant heterogeneous resources [19], which is conducive to exploratory innovation. However, the higher the patent stock, the stronger a firm's foundation, which might bring about core rigidity [20] and hinder exploratory innovation. These factors could moderate the association between partners' centrality and exploratory innovation, both independently and jointly. Thus, we further probe the moderating effects of patent stock and SHs, as well as their interaction.

This study examines data on the patents and joint publications of 194 Chinese pharmaceutical firms spanning 2007–2021 using multiple negative binomial regression models. In the pharmaceutical and biotechnology industries, firms rely heavily on the commercialization of scientific discoveries, and the correlation between scientific knowledge and innovation output is particularly strong [21]. Therefore, those industries can provide an especially useful context for examining the relationships among partners in scientific publications, networks, and firms' exploratory innovation [9]. China's pharmaceutical industry focuses on drug R&D and production. The products include chemical drug formulations, chemical raw materials, biopharmaceuticals, traditional Chinese medicine decoctions, traditional Chinese medicine preparations, pharmaceutical excipients, and packaging materials. In recent years, Chinese pharmaceutical companies have paid more attention to R&D for innovative drugs, and the government has implemented a special drug R&D funding program [22]. Patent approval and new drug discovery both rely on cutting-edge scientific knowledge [23,24], which stems from the spillover of partners' social capital in scientific collaboration networks and the unique resources of the firms themselves.

This research advances the literature on scientific collaboration and technological innovation in two ways. First, previous studies have mainly tested the influence of first-order social capital in scientific collaboration on technological innovation; this study, meanwhile, focuses on partners' centrality, which is an important type of second-order social capital in scientific collaboration. We show that partners' centrality in scientific collaboration boosts the focal firm's exploratory innovation. The empirical results broaden our understanding of the function of second-order social capital in scientific collaboration. Second, we examine the differentiated and joint moderating effects of patent stock and SHs on the relationship between partners' centrality in scientific collaboration and exploratory innovation. The findings show that patent stock diminishes the beneficial effects of partners' centrality on exploratory innovation. SHs also reduce the advantages of partners' centrality for exploratory innovation. Moreover, patent stock and SHs jointly influence this relationship, whereby partners' centrality has a more positive influence on exploratory innovation when the firm's patent stock is low and occupies fewer SHs. These findings deepen our understanding of the match between them and offers insights into the effect boundaries of second-order social capital under the resource-based view.

2. Theoretical background

Researchers have been studying corporate scientific collaboration networks for nearly 30 years. Studies have examined the form of scientific collaboration networks [25–27], their formation [28], their evolution [29], and their effects [4,8–11] at the individual [8], organizational [4,9–11,25,26,29], and regional levels [27,28]. Many suggest that firm innovation benefits from the amount of individual-level collaborative interaction between researchers employed by the focal firm and those with academic affiliations [8], as well as from the firm's network embedding in scientific collaboration [4,9–11]. McKelvey and Rake, for example, found that firms' product innovation in the domain of cancer benefits from the overall number of collaboration partners and indirect links in the copublication network, such as biotechnology companies and academic institutions [9]. Belderbos et al. found that pharmaceutical firms with strong scientific absorptive capacity showed a more pronounced correlation between their innovative performance and direct collaborative partnerships with universities [11]. Yang et al. suggested that a firm's innovation performance benefits from a strong and broad scientific collaboration network, with the benefits reinforced by technological dynamics and weakened by market dynamics [4]. Wang and Jiao found that the technological innovation performance of pharmaceutical firms is directly supported by SHs and degree centrality in an inverted U-shaped manner, while patent stock strengthens the former's effect, and collaboration strength positively moderates the effect of the latter [10]. Most of these studies adopted an ego-centric perspective, focusing on first-order social capital and viewing partners as homogeneous.

Others, meanwhile, adopt an altercentric perspective, noting the differences in social capital among partners and focusing on the effect of second-order social capital. Based on social network analysis, the structural characteristics of partners serve as the focal firm's second-order social capital [14]. This area of study is based on the premise that the network structure of partners is indicative of the caliber of resources and support available to a firm via its social network connections [15]; this has been validated at both the organizational and individual levels. At the individual level, the focal actor's value, creativity, and innovative behavior are influenced by the network positions of others [12,16,30]. Galunic et al. [12] found that connections with individuals of superior status or those in leadership positions in a network enhance the focal actor's capacity to create value. Hirst et al. suggested that individual creativity is supported by indirect network efficiency [16]. Grosser et al. showed that the average creative self-efficacy of others in the problem-solving network of employees improves their innovation behavior [30]. At the organizational level, partners' centrality [13], the diversity of partner's centrality [14,15], and the second-order social capital of customers and suppliers [31] affect firms' innovation performance. Karamanos found that a focal firm's exploratory innovation is strengthened by the centrality of its partners in technology alliances since it gains valuable insights through the observation and assessment of the actions and innovation results of its central partners [13]. Jiang et al. found that the diversity of partners' centrality in a firm's board-interlock network has a positive correlation with innovation performance [15]. Fang et al. suggested that partners' status benefits both tacit and explicit knowledge sharing [32]. Zhao et al. [31] suggested that green exploratory innovation and exploitative innovation are the benefits of the second-order social capital of both customers and suppliers. Wang et al. found that the association between partners' centrality diversity and a focal firm's exploratory innovation has an inverted U shape [14]. Zhang et al. [33], however, found that alliance partners exert a relatively weaker effect on exploratory innovation compared with that on exploitative innovation. Aggarwal suggested that the knowledge-based resources of a focal firm's partners might become overburdened as a result of competing demands for these resources from partners' partners [34]. Some studies, meanwhile, have used second-order social capital as a metaphor. Martínez Ardila et al. [35] found that firms' innovative performance has a positive quadratic relationship with second-order technological distance. These studies mainly focused on the second-order social capital of individual social networks, employees' problem-solving networks, technology alliance networks, and board-interlock networks without considering scientific collaboration networks. In addition, there is controversy regarding the effect of second-order social capital at the organizational level on exploratory innovation. Some suggest it is beneficial for technological exploration [14], others find that its effect is not strong [17], and some even propose that it will lead to network congestion [34].

In summary, there is ample room for further research on the effect of second-order social capital in scientific collaboration on exploratory innovation. Unlike technological alliances and board-interlock networks, scientific collaboration is more open and closer to the forefront of knowledge [4], which is important for firms in science-driven industries. Taking the US pharmaceutical industry as an example, the publications of large pharmaceutical corporations notably rose between 1990 and 2009, with a growing trend of collaboration between company scientists and external researchers [36]. Meanwhile, firms that focus more on exploration are adept at recognizing nascent innovations, conceiving alternative future possibilities, devising novel approaches to tasks, and identifying new opportunities [37]. Moreover, the logic of technological exploration is similar to that of scientific discovery. Thus, following Karamanos [13] and Jiang et al. [15], we suggest that partners' centrality in scientific collaboration is important second-order social capital for a focal firm and might have spillover effects on its technological exploration.

In technological exploration, firms need the support of both internal and external resources. The resource-based view suggests that resources can be categorized into three main types: physical, human, and organizational [38]. R&D resources can be obtained both internally and externally, facilitating technological transformation [39] and affecting innovation. In reality, firms' R&D resources vary, leading to technological differences between them and constituting the boundaries of technological exploration. Lai and Chen [40] noted the interplay between R&D resources, network centrality, and network density, which collectively contribute to enhancing

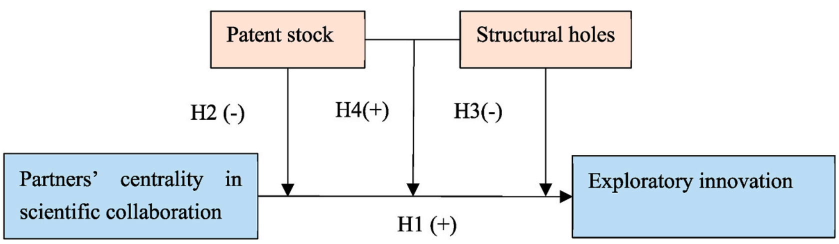

Fig. 1. Theoretical framework.

technological diversity. Studies show that both SHs and patent stock have significant effects on technological exploration [19,20]. Occupying SHs in the network exposes the focal firm to rich heterogeneous resources [19] and provides access to nonredundant information and knowledge flows through cognitive search [13], thus encouraging exploratory innovation. However, the effects of patent stock are relatively complex. On the one hand, a higher patent stock means rich technical knowledge—the foundation for the advancement of novel technologies. On the other hand, it will bring core rigidity, which hinders exploratory innovation [20]. Patent stock is an important internal resource for firms, while SHs serve as bridges connecting external resources that might become boundaries for partners' centrality in scientific collaboration and affect firms' technology exploration.

Based on the above analysis, we examine the effect of partners' centrality in scientific collaboration on a focal firm's exploratory innovation, along with the moderating roles of patent stock and SHs, individually and jointly. We explore the effect of a focal firm's second-order social capital in scientific collaboration on its technology exploration and the boundary effect of resources on this effect. Fig. 1 depicts the conceptual framework and hypotheses that are elaborated below.

3. Hypothesis development

3.1. *Partners' centrality in scientific collaboration and exploratory innovation*

Networked scientific collaboration provides opportunities for firms to access cutting-edge scientific knowledge and leading scientists. Previous studies examined the effect of a focal firm's position and connections in scientific collaboration networks on innovation [4,9,10], viewing the social capital of partners as homogeneous. In reality, however, partners might have different social capital, and in social networks, some partners are in the center, while others are on the periphery. In academic contexts, partners' influence is also different, and their social capital is the focal firm's second order [12], which we define from an organizational perspective—that is, partners' centrality in scientific collaboration networks.

Partners' centrality supports firms' exploratory innovation in three ways. First, high partners' centrality increases the size of the scientific knowledge spillover pool—namely, the unintentional dissemination of knowledge among firms without remuneration [41]. As partners' centrality increases, the focal firm obtains more recombinatorial opportunities to create new knowledge [42]. Moreover, according to the cognitive research model, a focal firm with higher partner centrality can increase the efficiency [13] of exploratory innovation by locating potentially worthy knowledge elements, identifying redundant factors, recombining the focal firm's knowledge with that of its partners', and providing insights into the focal firm. Second, central partners in scientific collaboration networks might enjoy high academic status, bringing the focal firm several benefits, including high-quality resources, legitimacy, and reputation [43]. High-quality resources facilitate the exploration of new technological opportunities; meanwhile, legitimacy and reputation help the focal firm attract more technical talent and high-quality partners. Furthermore, partners' centrality enhances firms' technological innovation quality. Third, higher partner centrality means more interactions with different ideas [31]. Such interactions facilitate the divergent thinking of technicians and improve the absorptive capacity of the focal firm, which in turn are likely to enable the generation of new ideas. In addition, some studies found that firms' exploratory innovation benefits from partners' centrality in alliances [13]. Partners' centrality in scientific collaboration gives firms access to a large spillover knowledge pool, high-quality resource profiles, and high-level scientific and technological personnel, all of which can promote the focal firm's exploratory innovation. We therefore propose the following.

H1. Partners' centrality in scientific collaboration positively affects a focal firm's exploratory innovation.

3.2. *Patent stock contingencies*

Patent stock refers to the number of patents a firm has amassed over a period of time, comprising an important knowledge stock [20]. More patent stock means the firm has a stronger technological knowledge foundation. Patent stock has both positive and negative effects on innovation. On the one hand, a large number of patents means that firms have rich experience in technology development and master more technological knowledge. It enhances their technological absorption, improving their ability to explore and identify knowledge from the environment [44,45] and generate accumulated competitive advantage, thus promoting technological exploration. On the other hand, patent stock might create negative path dependence [20]. For example, Leonard-Barton suggested that managers discontinue challenging development projects because of internal conflicts arising from mismatches between new and existing knowledge [46]. In this way, patent stock hurts innovation output [20].

When the patent stock and partners' centrality work together on exploratory innovation, the former is an internal source of new technology, while the latter is an external source of scientific knowledge, and they might replace each other. Although the accumulation of experience and technical knowledge can guide the development of scientific knowledge, engaging in two different types of innovation activities (i.e., science and technology) at the same time will bring high switching costs [47], thus hindering technology exploration. In addition, the absorption of scientific knowledge from external sources and the accumulation of internal technical knowledge might have comparable effects on technology exploration, resulting in similar innovation results. Thus, there are potential scope diseconomies, which means the efficiency of participating in different innovation activities at the same time is not as good as focusing on a single innovation activity [48]. Caloghirou et al. [49] found that firms with limited knowledge stock experience garner greater advantages from the development of knowledge flows from universities in innovation, especially those in industries close to university knowledge and in regions with social trust. We therefore propose Hypothesis 2.

H2. Patent stock negatively moderates the relationship between partners' centrality in scientific collaboration and a focal firm's exploratory innovation.

3.3. SH contingencies

SHs measure the degree to which partners in an actor's collaboration network are disconnected from each other [13,50,51]. Studies suggest that firms occupying SHs can benefit from receiving less redundant information, thereby better understanding opportunities and seeing new ones created by other groups [50]. In addition, more SHs means fewer restrictions from partnerships, which improves the efficacy of knowledge exploration [52]. Moreover, firms occupying SHs also have information control advantages owing to weak communication among network members [50,53]. In the scientific cooperation network, firms that occupy SHs can also access diverse scientific knowledge and gain advantages in information control [10], thus promoting exploratory innovation. As the level of SHs rises, however, the focal firm's exploratory innovation might face diminishing returns. High SHs means a lot of nonredundant information, which requires firms to invest effort in acquiring, processing, and integrating information [54]. Moreover, the overoccupation of SHs hinders trust between the focal firm and its collaborators, which might lower the firm's reputation and decrease the possibility of knowledge transfer [51]. In addition, the focal firm must shift a lot of time and personnel to ensure the operation of scientific collaboration when it occupies higher SHs, incurring decision-making, coordination, and control costs.

SHs are a type of first-order social capital, and partners' centrality is a type of second-order social capital, and they might swap roles. The heterogeneous knowledge and information control advantages of SHs are similar to the knowledge spillover advantages and absorption capabilities of partners' centrality in exploratory innovation. Owing to the limitations of network position, normal actors often lack SHs, and they are limited by homogeneous knowledge and information, with fewer actual and potential resources (social capital) [55]. If these firms have a high degree of partners' centrality, they can overcome their network weaknesses and maximize the role of partners' centrality in fostering exploratory innovation. However, if a firm has high SHs and high partners' centrality, it will obtain a great deal of direct and indirect resources, as well as heightened communication and coordination costs, which reduce absorption efficiency and hinder technological exploration. Thus, we put forward the following.

H3. SHs have a negative moderating effect on the association between partners' centrality in scientific collaboration and a focal firm's exploratory innovation.

3.4. Joint effects of patent stock and SHs

We suggest that, in addition to their respective effects, patent stock and SHs jointly affect the relationship between firms' exploratory innovation and partners' centrality. In scientific collaboration, patent stock and SHs complement each other, and firms occupying SHs can overcome path dependence and better utilize patent stock, which helps improve innovation performance [10]. Compared with other situations, when firms have lower patent stock but do not occupy SHs in scientific collaboration, partners' centrality has the greatest marginal effect on exploratory innovation. Since such firms are generally located on the periphery of the network, lacking resources and having low technical exploration capacity, they need a rich pool of scientific knowledge spillover, high absorption capacity, and high-quality technical talent. If influential partners can be found, exploratory innovation will be improved. When a firm has high patent stock and less SHs, partners' centrality has a detrimental effect on exploratory innovation, since the negative effect of path dependence brought about by the patent stock cannot be offset or surpassed by the positive effect of high partners' centrality. The main determinants for addressing a state of lock-in include regulatory measures, technological niches and diversity, strategic shifts at the firm level, and the involvement of lead users [56]. However, partners' centrality only exerts a slight effect on these factors. In light of the above, we propose Hypothesis 4.

H4. Patent stock and SHs have a joint effect on the relationship between partners' centrality in scientific collaboration and a focal firm's exploratory innovation; that is, the positive effect of partners' centrality on exploratory innovation is more pronounced when both patent stock and SHs are low.

4. Method

4.1. Sample firms and data collection

The sample firms we use to test our hypotheses are listed Chinese pharmaceutical companies, spanning 2007–2021. This sample is suitable for this research because, first, pharmaceutical firms rely to a large extent on the commercialization of scientific discoveries [21]. However, owing to limited internal R&D capabilities, collaborating with universities, research institutes, and hospitals is an important way for Chinese pharmaceutical companies to participate in scientific research [57]. Second, patents are an important component of the intellectual property strategies of pharmaceutical companies since they face high costs and risks. Applying for patents can serve as a strong barrier for pharmaceutical companies, creating market exclusivity that allows them to maximize revenue from new drugs, thereby driving further innovation [58]. As in previous studies [9], our data mainly comprise publications and patents. After removing 107 companies that are SST, ST, *ST, or S.ST; belong to the SSE star market; or have been engaged in the pharmaceutical industry for less than 2 years, we capture the financial indicators and basic information of 194 publicly traded pharmaceutical companies from the CSMAR database. Then, following Belli and Baltà [59], we select copublication data from the Web of Science Core Collection database, encompassing various document types such as articles, proceedings, reviews, and meeting abstracts. We also collect articles from CNKI academic journals that are indexed in SCI, EI, CSSCI, CSCD, and Peking University's core periodical catalog. We obtain 3481 Chinese-language papers and 611 English-language papers spanning 2005–2021 with searched affiliations belonging to sample pharmaceutical firms. Following Yang et al. [4], we use a five-year window to build scientific collaboration networks. Additionally, we collect patent data from the CNIPA database.

4.2. Variables

4.2.1. Dependent variable

Following Wen et al. [60], we measure exploratory innovation by the amount of exploratory four-digit IPC classes registered by firm i in the years t+2 and t+3. A class is categorized as exploratory innovation if the firm did not apply for patents in that class in the previous 5 years [52]. We use a five-year window because it is a suitable time frame for evaluating the technological influence of previous inventions [51].

4.2.2. Independent variables

Partners' centrality equals the average degree centrality of a focal firm's partners [13]. We weigh degree centrality by the number of direct links to the focal organization between year t−2 and t+2. Patent stock equals the number of invention patents granted to the focal firm prior to year t. SHs indicate the degree of network redundancy [19]. Following Chen et al. [61], SHs are calculated using the SNA software UCINET 6.2 as follows [62]:

$$SH_i = 1\text{-}\sum_{j}\left(p_{ij} + \sum_{q\neq i\neq j} p_{iq}p_{qj}\right)^2, \tag{1}$$

where p_{ij} denotes the share of relations of node i devoted to connecting node j. The sum in the parentheses is the percentage of node i's path, which is directly or indirectly endowed in the link with node j in the network. We subtract the aggregate constraint from 1 to represent the focal firm's advantages of spanning SHs.

4.2.3. Control variables

According to previous research [10,63,64], most firm attributes should be controlled. Table 1 shows the measurements of the variables.

5. Results and analysis

Table 2 presents the intercorrelation matrix and descriptive statistics of the major variables in our model, including the mean, standard deviation, variance inflation factors (VIFs), and correlation coefficients. It can be seen that the correlation coefficients between the primary variables are below 0.7, suggesting that discriminant validity is not an issue in the model. VIFs are less than 10, indicating that the level of multicollinearity is acceptable. To further avoid potential multicollinearity, we standardize the interaction terms ahead of the regression analysis [65]. The dependent variable in this study, exploratory innovation, is classified as a count variable. After statistical analysis, we found that the variance value of exploratory innovation is 22.213, while the mean value is 2.460.

Table 1
Variable measurement.

Variable		Measurement
Dependent	Exploratory innovation	Total number of exploratory patents filed by the focal firm from year t+2 to t+3
Independent	Partners' centrality	Average degree centrality of partners from year t−2 to t+2
	Patent stock	Number of invention patents granted to the focal firm before year t
	Structural holes	Degree of redundancy in the scientific collaboration networks from year t−2 to t+2
Controls	Collaboration strength	Average number of copublications between the focal firm and its partners from year t−2 to t+2
	Degree centrality	Number of direct links to the focal firm from year t−2 to t+2
	Publications	Number of papers published by the focal firm before year t
	R&D intensity	R&D expense/sales revenue
	Size	Logarithm of total assets
	Age	Time span from the founding of the firm to year t
	SOE	Dummy variables with a value of 1 representing yes and 0 meaning no
	R&D subsidy	R&D subsidy amount; unit is 10,000 yuan
	Export	Dummy variables where 1 denotes yes and 0 signifies no
	ROA	Dividing net profit into average total assets
	Leverage	Dividing total debt into total assets
	Year	Binary variables (2008–2019) where a value of 1 means yes and 0 no
	Region	Categorical variables, such as those representing China's different regions (e.g., northeast, central, western), are encoded as dummy variables, with a value of 1 indicating the presence of a particular characteristic and 0 indicating its absence
	Industry	Dummy variables include traditional Chinese medicine pharmacy and chemical pharmacy in which a value of 1 means yes and 0 no

Table 2
Correlations and descriptive statistics of the major variables.

Variables	Mean	SD	VIF	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Exploratory innovation	2.460	4.713	–	1.000														
2 Partners' centrality	10.705	10.542	1.25	0.026	1.000													
3 Patent stock	31.630	58.867	1.61	0.079[c]	0.206[c]	1.000												
4 Structural holes	0.627	0.319	1.14	−0.006	−0.140[c]	0.164[c]	1.000											
5 Collaboration strength	0.980	0.654	1.09	0.010	−0.033	0.083[c]	0.156[c]	1.000										
6 Degree centrality	9.044	15.750	2.09	0.067[b]	0.124[c]	0.430[c]	0.226[c]	0.035	1.000									
7 Publications	12.034	33.663	1.99	0.088[c]	0.100[c]	0.500[c]	0.182[c]	0.126[c]	0.587[c]	1.000								
8 R&D intensity	5.537	5.049	1.26	−0.009	0.100[c]	0.099[c]	0.053[a]	0.068[b]	0.131[c]	0.084[c]	1.000							
9 Size	21.766	0.996	2.25	0.071[c]	0.236[c]	0.354[c]	0.065[b]	−0.011	0.274[c]	0.227[c]	−0.050[b]	1.000						
10 Age	17.534	5.609	1.76	0.012	0.185[c]	0.074[c]	−0.006	−0.063[b]	0.101[c]	0.152[c]	−0.020	0.390[c]	1.000					
11 SOE	0.263	0.441	1.21	0.036	−0.106[c]	−0.049[b]	0.047[a]	0.049[a]	−0.029	0.069[c]	−0.184[c]	0.154[c]	0.052[b]	1.000				
12 R&D subsidy	2732.31	4713.4	1.63	0.030	0.208[c]	0.232[c]	0.072[b]	−0.023	0.225[c]	0.122[c]	0.056[b]	0.567[c]	0.227[c]	0.054[b]	1.000			
13 Export	0.517	0.500	1.22	−0.044[a]	0.089[c]	0.017	−0.017	0.014	0.029	0.008	0.024	0.248[c]	0.108[c]	0.051[b]	0.139[c]	1.000		
14 ROA	0.069	0.072	1.49	0.099[c]	−0.042	0.028	0.058[b]	0.051[a]	0.135[c]	0.040[a]	−0.053[b]	−0.009	−0.074[c]	−0.079[c]	0.013	−0.053[b]	1.000	
15 Leverage	0.309	0.181	1.73	−0.030	−0.099[c]	0.104[c]	0.062[b]	−0.017	−0.024	0.035	−0.090[c]	0.270[c]	0.119[c]	0.265[c]	0.189[c]	0.150[c]	−0.432[c]	1.00

Note.
Statistics for the rest of the control variables can be obtained by contacting the corresponding author.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

The variance value is significantly greater than the mean value, indicating that the dependent variable is overdispersed. Thus, the suitable method for testing our hypotheses is negative binomial regression. Given that the model uses random effects and fixed effects to handle the panel data, we select several models based on the Hausman specification [66].

Table 3 presents the regression analysis results for our theoretical framework. We use five models to test the hypotheses.

The base model indicates that exploratory innovation significantly benefits from two factors: firm age ($\beta = 0.033$, $p < 0.05$) and ROA ($\beta = 2.325$, $p < 0.05$). This aligns with previous studies. Moreover, model 1 shows that partners' centrality has a notable and positive effect on exploratory innovation ($\beta = 0.012$, $p < 0.05$), indicating that partners' centrality, as important second-order social capital, contributes to focal firms' pursuit of exploratory innovation. Thus, H1 is supported.

Model 2 reveals the moderating effect of patent stock on the relationship between partners' centrality and exploratory innovation. The results indicate that the interaction term between partners' centrality and patent stock exhibits a significant negative coefficient ($\beta = -0.178$, $p < 0.01$). Fig. 2 illustrates the moderating effect of patent stock. As we can see, when the focal firm possesses a higher patent stock, the marginal effect of partners' centrality on exploratory innovation is reduced or can even become negative. This suggests that the positive effect of partners' centrality on firms' exploratory innovation will be weakened by higher patent stock, which extends existing findings. In addition, the coefficient of partners' centrality * patent stock is also significantly negative ($\beta = -0.301$, $p < 0.01$) in model 4. Hence, H2 is supported.

Model 3 presents the moderating effect of SHs. The coefficient of partners' centrality * structural holes is notably negative ($\beta = -0.099$, $p < 0.01$). Fig. 3 depicts the moderating effect of SHs on the relationship between exploratory innovation and partners' centrality. The marginal effect of partners' centrality on exploratory innovation is greater when the focal firm has lower SHs, indicating that partners' centrality enhances firms' exploratory innovation, and this positive effect is negatively moderated by SHs, which extends the current literature. Hence, H3 is supported.

Model 4 presents the joint effects of patent stock and SHs, showing that the coefficient of partners' centrality * patent stock * structural holes is positive significantly ($\beta = 0.144$, $p < 0.1$). Fig. 4 depicts the joint effects of patent stock and SHs. It can be seen that a smaller patent stock and lower SHs will reinforce the beneficial effect of partners' centrality on businesses' exploratory innovation, because the positive slope of partners' centrality on exploratory innovation is steeper. This broadens our understanding of the influence boundary of second-order social capital. Hence, H4 is supported. Meanwhile, the slope of partners' centrality on exploratory innovation is negative when the focal firm has a higher patent stock and lower SHs. This means that without the support of higher SHs, firms with a higher patent stock cannot benefit from rich second-order social capital, and it might even be harmful.

Moreover, Fig. 5 shows the marginal effect of partners' centrality under the combined influence of patent stock and SHs. As we can see, the marginal effect of partners' centrality on exploratory innovation diminishes as patent stock increases, and this decline is not

Table 3
Partners' centrality in scientific collaboration and exploratory innovation: Roles of patent stock and structural holes.

Variables	Base model	Model 1	Model 2	Model 3	Model 4
Collaboration strength	−0.063	−0.053	−0.051	−0.060	−0.055
Degree centrality	0.003	0.002	0.006	0.003	0.003
Publications	−0.0003	−0.0003	0.001	−0.0003	0.001
R&D intensity	−0.006	−0.008	−0.009	−0.008	−0.009
Size	0.028	0.005	−0.011	−0.019	−0.025
Age	0.033[b]	0.037[b]	0.036[b]	0.037[b]	0.035[b]
SOE	0.062	0.085	0.082	0.087	0.079
R&D subsidy	−4.38e-07	−9.41e-07	5.20e-06	1.67e-07	8.23e-06
Export	0.100	0.115	0.143	0.121	0.151
ROA	2.325[b]	2.506[c]	2.484[c]	2.362[b]	2.581[c]
Leverage	0.285	0.332	0.473	0.310	0.451
Partners' centrality		***0.012***[b]	***0.251***[c]	***0.158***[c]	***0.248***[c]
Patent stock			−0.028		−0.020
Structural holes				***0.102***[a]	***0.130***[b]
Partners' centrality × patent stock			***−0.178***[c]		***−0.301***[c]
Partners' centrality × structural holes				***−0.099***[c]	0.034
Patent stock × structural holes					0.026
Partners' centrality × patent stock × structural holes					***0.144***[a]
Constant	−0.989	−0.622	−0.090	−0.116	0.219
Industry	included	included	included	included	included
Year	included	included	included	included	included
Region	included	included	included	included	included
No. of firms	153	153	153	153	153
No. of observations	858	858	858	858	858
Log-likelihood	−1747.502	−1744.489	−1734.133	−1739.002	−1729.434
Prob ≥ chibar2	0.000	0.000	0.000	0.000	0.000
Hausman test	RE, p = 0.550	RE, p = 0.364	RE, p = 0.481	RE, p = 0.626	RE, p = 0.686

Note.
Variations in the number of firms are attributable to missing data.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

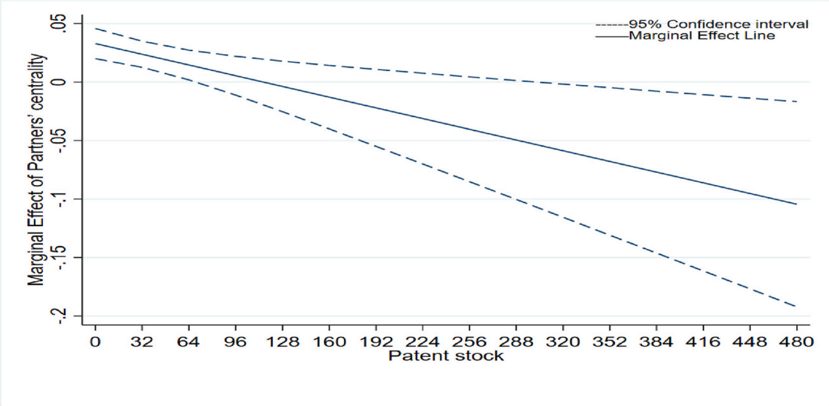

Fig. 2. Moderating effect of patent stock.

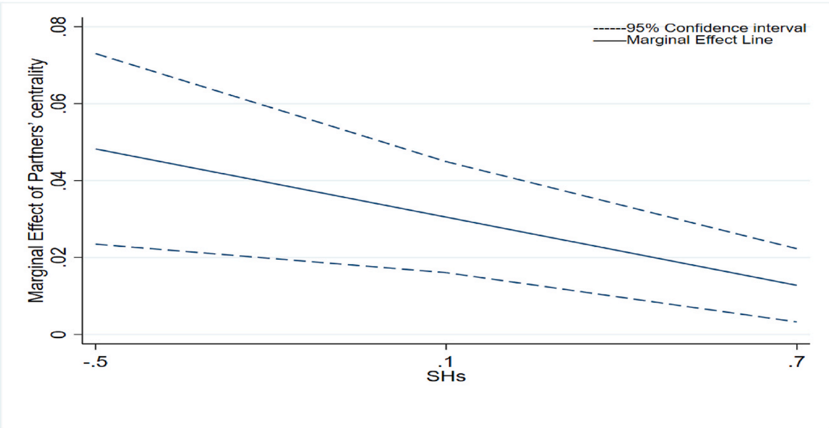

Fig. 3. Moderating effect of SHs.

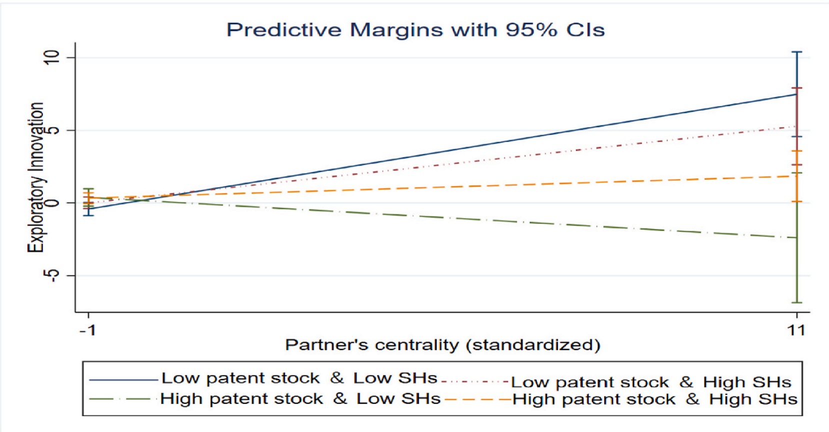

Fig. 4. Joint effects of patent stock and SHs.

reversed by the presence of higher SHs. In other words, the beneficial effect of influential partners on exploratory innovation is attenuated when patent stock and SHs act concurrently.

Next, we conduct several robustness checks. First, the Hausman test indicates that the negative binomial regression model with random effects is more appropriate for our research in models 1, 2, 3, and 4, as compared with the fixed-effects model. For robustness,

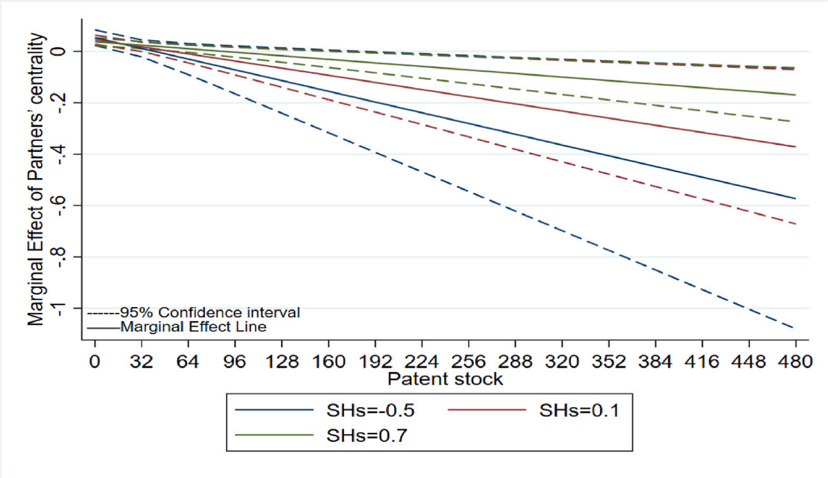

Fig. 5. Marginal effect of partners' centrality under the joint influence of patent stock and SHs.

we apply models with fixed effects in models 1, 2, 3, and 4 and find that the regression results are mostly steady.

Second, using partners' average efficiency size as a measure of partners' centrality, we find that the regression outcomes are also robust when using negative binomial regression with random effects (Table 4). Model 5 shows that the coefficient of partners' centrality is significantly positive ($\beta = 0.014$, $p < 0.05$). Model 6 indicates that the coefficient of partners' centrality * patent stock is significantly negative ($\beta = -0.173$, $p < 0.01$). Meanwhile, model 7 shows that the coefficient of partners' centrality * structural holes is significantly negative ($\beta = -0.098$, $p < 0.01$). In model 8, it can be seen that the coefficient of partners' centrality * patent stock * structural holes is significantly positive ($\beta = 0.146$, $p < 0.1$).

Third, we use the total number of exploratory innovations filed by the focal firm from year t+2 to t+3 using a four-year window as the dependent variable. Negative binomial regression with random effects is applied, as shown in Table 5. Models 9, 10, 11, and 12 show the separate moderating effects and joint effects of patent stock and SHs. Model 9 shows that the coefficient of partners' centrality is significantly positive ($\beta = 0.111$, $p < 0.05$), while model 10 shows that the coefficient of partners' centrality * patent stock is significantly negative ($\beta = -0.174$, $p < 0.01$). Model 11 indicates that the coefficient of partners' centrality * structural holes is also significantly negative ($\beta = -0.096$, $p < 0.01$). Meanwhile, model 12 indicates that the coefficient of partners' centrality * patent stock * structural holes is significantly positive ($\beta = 0.155$, $p < 0.05$).

In addition, using a panel Poisson regression model with random effects, we find that the results remain robust, as shown in Table 6. In model 13, we can see that the coefficient of partners' centrality is significantly positive ($\beta = 0.012$, $p < 0.01$). Model 14 shows that the coefficient of partners' centrality * patent stock is significantly negative ($\beta = -0.195$, $p < 0.01$). In model 15, the coefficient of partners' centrality * structural holes is negative ($\beta = -0.034$, $p > 0.1$). Model 16 shows that the coefficient of partners' centrality * patent stock * structural holes is significantly positive ($\beta = 0.204$, $p < 0.01$).

Table 4
Results of replacing the independent variable.

Variables	Model 5	Model 6	Model 7	Model 8
Partners' centrality	***0.014***[b]	***0.230***[c]	***0.148***[c]	***0.217***[c]
Patent stock		−0.026		−0.014
Structural holes			***0.101***[a]	***0.122***[b]
Partners' centrality × patent stock		***−0.173***[c]		***−0.294***[c]
Partners' centrality × structural holes			***−0.098***[c]	0.030
Patent stock × structural holes				0.021
Partners' centrality × patent stock × structural holes				***0.146***[a]
Constant	−0.595	−0.278	−0.206	0.032
Controls: industry, year, and region	included	included	included	included
No. of firms	153	153	153	153
No. of observations	858	858	858	858
Log-likelihood	−1744.686	−1735.788	−1739.509	−1731.415
Prob ≥ chibar2	0.000	0.000	0.000	0.000
Hausman test	RE, p = 0.436	RE, p = 0.485	RE, p = 0.707	RE, p = 0.691

Note.
Variations in the number of firms are attributable to missing data.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Table 5
Results of replacing the dependent variable.

Variables	Model 9	Model 10	Model 11	Model 12
Partners' centrality	***0.111***[b]	***0.232***[c]	***0.142***[c]	***0.224***[c]
Patent stock		−0.038		−0.032
Structural holes			***0.098***[a]	***0.127***[b]
Partners' centrality × patent stock		***−0.174***[c]		***−0.308***[c]
Partners' centrality × structural holes			**−0.096**[c]	0.037
Patent stock × structural holes				0.048
Partners' centrality × patent stock × structural holes				***0.155***[b]
Constant	−0.290	0.052	0.054	0.319
Controls: industry, year, and region	included	included	included	included
No. of firms	153	153	153	153
No. of observations	858	858	858	858
Log-likelihood	−1770.598	−1760.731	−1765.501	−1755.751
Prob ≥ chibar2	0.000	0.000	0.000	0.000
Hausman test	RE, p = 0.271	RE, p = 0.169	RE, p = 0.260	RE, p = 0.234

Note.
Variations in the number of firms are attributable to missing data.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Table 6
Results of replacing the regression model.

Variables	Model 13	Model 14	Model 15	Model 16
Partners' centrality	***0.012***[a]	***0.241***[a]	***0.121***[a]	***0.248***[a]
Patent stock		***−0.489***[a]		***−0.494***[a]
Structural holes			−0.044	−0.003
Partners' centrality × patent stock		***−0.195***[a]		***−0.374***[a]
Partners' centrality × structural holes			−0.034	***0.141***[a]
Patent stock × structural holes				0.076
Partners' centrality × patent stock × structural holes				***0.204***[a]
Constant	2.324	0.132	2.356	0.241
Controls: industry, year, and region	included	included	included	included
No. of firms	153	153	153	153
No. of observations	858	858	858	858
Log-likelihood	−2109.022	−2059.287	−2107.615	−2047.886
Prob ≥ chibar2	0.000	0.000	0.000	0.000

Note.
Variations in the number of firms are attributable to missing data.
[a] $p < 0.01$.

In summary, our results have a satisfactory level of reliability.

6. Discussion and conclusion

We empirically examine the effects of partners' centrality in scientific collaboration networks on firms' exploratory innovation. We verify the hypotheses based on a sample of 194 Chinese pharmaceutical firms spanning 2007–2021, using copublication data from the Web of Science and CNKI to construct the scientific collaboration network. The regression results verify that partners' centrality enhances firms' exploratory innovation. Furthermore, patent stock mitigates the effect of partners' centrality on exploratory innovation. SHs also have a negative moderating effect on the relationship between partners' centrality and exploratory innovation. We further reveal that the influence of partners' centrality on exploratory innovation is mostly positive when both patent stock and SHs are low.

6.1. Theoretical contributions

First, this study enriches our understanding of the antecedent variables of firms' exploratory innovation by exploring the effect of partners' centrality, which is a significant dimension of second-order social capital. Previous studies considered the role of network embeddedness in scientific collaboration and its effect on innovation outputs [4,10,61]. Some highlighted spanning structural boundaries and improving relational capital as a means of optimizing innovation output [4,61]. Few, however, have examined the influence of second-order social capital in scientific collaboration on exploratory innovation. Since social capital has spillover effects [12], attention should be paid to second-order social capital. In addition, the social capital of different partners is heterogeneous [32].

Our study confirms the beneficial effect of partners' centrality in scientific collaboration on exploratory innovation and highlights the importance of high-quality partners in scientific collaboration, which expands existing findings in the scientific collaboration field.

Second, we contribute to the literature on the relationship between partner configuration and exploratory innovation by demonstrating the moderating effects of patent stock and SHs, individually and jointly. The findings reveal the function of partner configuration in fostering firms' exploratory innovation. When patent stock is low, the beneficial effect of partners' centrality becomes more pronounced; the same holds when SHs are low. We additionally show that the positive effect of partners' centrality on exploratory innovation is most significant when both patent stock and SHs are low. In this way, we provide new insights into the conditions under which businesses can benefit from the central role of partners in scientific collaboration for exploratory innovation.

6.2. Managerial implications

First, firms usually have diverse scientific collaboration strategies for exploratory innovation. In this process, managers are advised to fulfill the function of second-order social capital in scientific cooperation and be mindful of its positive spillover effects. If the focal firm aims to further explore new technology domains, managers might seek opportunities to collaborate with influential partners, which will give the focal firms access to a scientific knowledge spillover pool, improve absorption capacity, and attract high-quality scientific researchers.

Second, managers might focus on the matching between second-order social capital and firms' resources. Managers should check the patent stock; if the focal firm has a limited number of patents, it is important to fully leverage the potential positive effect of partners' centrality. However, if the patent stock of the focal firm is relatively high, the cost of maintaining or improving partners' centrality should also be measured, and other methods should be adopted to overcome path dependence. Meanwhile, managers also need to consider their structural positions in the scientific collaboration network. If more SHs are occupied, partners' centrality will replace each other, but if fewer SHs are occupied, partners' centrality will be further improved. In addition, managers should investigate partners' centrality, patent stock, and SHs together. If a firm has a low patent stock and low SHs, partners' centrality will have the strongest marginal effect on technological exploration compared with other situations. However, if a firm has a high patent stock and low SHs, partners' centrality hinders exploratory innovation.

6.3. Limitations and future research

First, we use the patents and IPC codes possessed by a focal firm to illustrate its exploratory innovation. However, not all technology resources are patented in the pharmaceutical industry and other science-based industries, even though patents and IPC codes are accepted as typical indicators for exploratory innovation. Firms might also possess security technologies that are not documented in patent records. Second, we test the hypotheses based on the scientific collaboration networks of pharmaceutical companies, since they are part of the knowledge-intensive sector in developing economies. Yet, the results and identified mechanisms might vary in other settings. Third, we derive the data on scientific collaboration from published papers but ignore other data sources, such as websites or social media and the network actors that Belli and Gonzalo-Penela focused on [67]. Thus, future research can, first, use more complete measurements to evaluate exploratory innovation, such as new drugs and the different stages of clinical trials. Second, the hypotheses can be tested in other settings, such as the United States or Japan, or in other industries, such as smartphones or automobiles, thus expanding the feasibility of the findings. Future studies could also explore the potential mechanism underlying the effects of scientific collaboration networks and examine the influence of other typical characteristics on exploratory innovation, such as the depth and breadth of collaboration, and partners' diversity. Finally, future research should focus on the digitalization of scientific research activities and obtain data on scientific collaboration from multiple sources.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Xingxiu Wang: Writing – review & editing, Writing – original draft, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xiaoli Zhong:** Writing – review & editing. **Huiying Jiao:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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