Front. Eng. Manag. 2025, 12(4): 1141–1156
https://doi.org/10.1007/s42524-025-4188-x

RESEARCH ARTICLE

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How innovation community embeddedness impacts firms' innovation performance: Evidence from the global 3D printing industry

Abstract The acceleration of digitalization and networking in the global landscape has been prompting organizations to connect into innovation communities beyond geographic boundaries within innovation ecosystems. These communities, consisting of firms that collaborate frequently, serve as a vital sub-environment for co-innovation and value creation. Despite the significant role played by these innovation communities, the impact of a firm's embeddedness within these communities on its innovation performance remains underexplored. This paper addresses this gap by examining the effects of both within-community and cross-community embeddedness on firm innovation, with a specific focus on the contingency of collaboration complementarity. We introduce a conceptual model analyzing the effects of both relational and structural embeddedness within and across communities. An empirical study is conducted using 22 years of panel data from the global 3D printing industry. We construct patent collaboration networks among 6,109 relevant organizations over 5-year windows and identify innovation communities in each network through topological clustering algorithms. A negative binomial regression model is employed to test our hypotheses. Our findings reveal that firms benefit from both within-community and cross-community embeddedness. Notably, firms with higher collaboration complementarity experience greater benefits from within-community relational embeddedness and cross-community structural embeddedness, while those with lower complementarity gain more from cross-community relational embeddedness. This research enriches the innovation ecosystem literature by introducing an innovation community perspective and highlighting how embeddedness, coupled with collaboration orientation, drives firm-level innovation. Additionally, it offers insights into how firms can leverage collaborations and optimize their positions within innovation ecosystems to enhance their innovation performance.

Keywords innovation ecosystem, innovation community, collaboration complementarity, 3D printing industry

Received Sep. 30, 2024; revised Jan. 26, 2025; accepted Feb. 7, 2025

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This work was supported by the National Natural Science Foundation of China (Grant Nos. 72272017, L2224047, 71974107, 71872019, and L2424237), the National Social Science Foundation of China (Grant No. 22AZD125), the Beijing Social Science Foundation (Grant No. 22GLA012), the Beijing University of Posts and Telecommunications Interdisciplinary Team Program for the 'Double First-Class' Initiative (No. 2023SYLTD11) , the Construction Project of China Knowledge Center for Engineering Sciences and Technology (No. CKCEST-2023-1-7), the National Social Science Foundation of China, and the HSE University Basic Research Program.

1 Introduction

The acceleration of digitalization and networking in the global landscape has encouraged organizations to cluster together regardless of geographic boundaries, leading to the emergence of innovation communities in innovation ecosystems. An innovation community comprises a network of organizations, which collaborate closely for value co-creation. In this context, firms are embedded not only in the broader innovation ecosystem but also in these innovation communities, which serve as vital incubators for innovation. Intensive interactions within innovation communities foster collective identity and build mutual trust (Georgiou and Arenas, 2023; Wu et al., 2024). They can also lead to homogeneous thinking (Gu et al., 2023). Although interactions across different innovation communities introduce valuable diversity in perspectives and heterogeneous knowledge (Clement et al., 2018), these cross-community connections are often associated with substantial coordination and integration costs (Sytch and Tatarynowicz, 2014). These tensions raise a critical question we postulate as research questions: How should firms be strategically embedded in innovation communities to enhance innovation, particularly with varying collaborative orientations in the ecosystems?

The existing literature has not yet directly explored innovation community embeddedness. While a few studies examine the implications of community-level characteristics, such as resource foundation and membership dynamics (Upham et al., 2010; Wang and Lu, 2021), innovation community embeddedness has been largely neglected, particularly the distinctions between within-community and cross-community. Drawing on social network theory (Granovetter, 1985), embeddedness can be explored in terms of relational and structural dimensions. However, findings on the relationship between a firm's embeddedness and its innovation outcomes are inconsistent. They are reported as positive (Schilling and Phelps, 2007; Gonzalez-Brambila et al., 2013), negative (Balachandran and Hernandez, 2018), or even inverted U-shaped (Zhang et al., 2019). Crucial insights may arise when exploring how firms' innovation community embeddedness influences their innovation.

Moreover, collaboration complementarity in the innovation ecosystem deserves deeper exploration as a contingency. Complementarity is a crucial characteristic in an innovation ecosystem (Kapoor, 2018; Shipilov and Gawer, 2020), which refers to firms complementing each other's needs for value co-creation. The alignment between collaboration complementarity and firms' embeddedness in the ecosystem is crucial for fostering innovation. Current studies explain that firms' embeddedness provides potential opportunities for enhancing innovation (Soda et al., 2018, 2019). Whether these opportunities are realized or not is largely determined by the extent to which embeddedness fits with the collaboration orientation in the innovation ecosystem. While some firms may be influenced by an innovation culture characterized by the Not-Invented-Here Syndrome (Hannen et al., 2019), we argue that this influence is less significant in our study. The firms analyzed here are, to some extent, embedded in innovation ecosystems, which fosters openness to respecting and anticipating external inspirations and solutions. In this sense, given the varying degrees of collaboration complementarity, it is imperative to investigate how these differences influence the relationship between a firm's embeddedness and its innovation performance.

Therefore, this paper aims to answer the research questions by illustrating how innovation community embeddedness impacts firms' innovation performance. To explore the mechanism, this study proposes a conceptual model and hypotheses concerning the effects of within-community and cross-community embeddedness on innovation, with consideration of the contingency of collaboration complementarity. We conduct the empirical study in the global 3D printing industry using 22-year panel data. Based on collaboration networks covering 6,109 organizations, innovation communities are identified by topological clustering methods. Collaboration complementarity is also measured quantitatively by natural language processing methods.

Our research contributes to innovation ecosystem theory in three ways. First, by examining the differences between within-community and cross-community innovation communities, we advance the understanding of how innovation community embeddedness shapes firms' innovation performance. Second, we demonstrate how different collaboration orientations influence the relationship between community embeddedness and firm innovation, echoing Shipilov and Gawer's (2020) emphasis on collaboration characteristics in network and ecosystem research. Third, we also provide methodological insights by employing topological clustering to identify innovation communities and natural language processing to measure collaboration complementarity. By opening the black box of innovation communities, collaboration complementarity, and innovation performance, our findings provide guidance to managers on how to improve innovation performance through innovation community embeddedness and to policymakers to understand how the firm's innovation performance evolves. The latter is a valuable insight for future targeted innovation policy making.

2 Theory and hypotheses

With the trend of networking and agglomeration, organizations with close collaborations establish partnerships beyond physical restrictions and cluster into innovation communities thereby entering or developing ecosystem(s). Like biological communities in the ecosystem, innovation communities emerge as distinctive sub-environments for collaboration and value creation, making a paradigm shift in innovation. Firms are embedded not only in the ecosystem but also in the community to share resources and foster innovation, which reshapes the innovation landscape.

A literature review reveals a significant gap in research examining innovation community embeddedness. Early studies treat the innovation community as a whole, focused primarily on how community influences firm behaviors and innovation outcomes. They generally assume that organizations embedded within the same community have shared characteristics, such as density (Iurkov et al., 2023), knowledge foundation (Upham et al., 2010), and membership turnover (Wang and Yang, 2019; Wang and Lu, 2021). In reality, organizations are inherently distinct, each exhibiting unique patterns of embeddedness that shape their individual paths to innovation. Furthermore, the innovation community can also serve as a boundary to divide the embeddedness. Within communities, firms tend to be similar and homogeneous due to intensive relationships (Wu et al., 2024). Conversely, firms from different communities show heterogeneous identities due to sparse connectivity (Sytch and Tatarynowicz, 2014; Clement et al., 2018). This distinction establishes two critical aspects, within-community embeddedness and cross-community embeddedness, depending on whether the focal firm is surrounded by a group of similar or diverse organizations. The division is crucial for a more nuanced understanding of how innovation communities shape their innovation outcomes but has been neglected in the literature.

To examine innovation community embeddedness thoroughly, the insight from social network theory, particularly Granovetter's distinction between relational and structural embeddedness (Granovetter, 1985), offers a coherent framework. This framework is beneficial for organizing arguments of innovation community embeddedness. However, empirical results reported in the literature regarding the performance implications of embeddedness are inconsistent. Some studies show that relational embeddedness enhances innovation performance (Ahuja, 2000; Han et al., 2020), yet others indicate it might hinder innovation (Fleming et al., 2007) or have no significant impact (Gonzalez-Brambila et al., 2013). Similarly, the effects of structural embeddedness on innovation development have also been found to be negative (Obstfeld, 2005), positive (Han et al., 2020), or inverted U-shaped (Yan et al., 2019; Xu et al., 2023), with some studies reporting to be not significant (Mazzola et al., 2015). In this light, these conflicting findings highlight the need for a deep understanding of how innovation community embeddedness affects firm innovation.

To better understand how innovation community embeddedness influences innovation and address these inconsistencies, we develop the conceptual framework and propose hypotheses (see Fig. 1). A firm's innovation community embeddedness refers to its relationship portfolio of collaborations with other organizations, which can be categorized as either within the same community or across diverse communities. Furthermore, by drawing on existing literature (Granovetter, 1985), the embeddedness can be explored through both relational and structural dimensions. This provides a thorough insight into how innovation community embeddedness influences innovation.

2.1 The effects of innovation community embeddedness

2.1.1 Within-community embeddedness

Within-community embeddedness highlights how firms are embedded in a group of actors belonging to the same community, which is characterized by similar behavioral patterns. These shared - but not identical - patterns manifest in various ways, including organizational cultures, technological and market opportunities, and strategies to capitalize on these chances. This cultivates a shared identity and fosters trust among its members (Ter Wal et al., 2016).

Firms' innovation performance will benefit significantly from within-community relational embeddedness, which

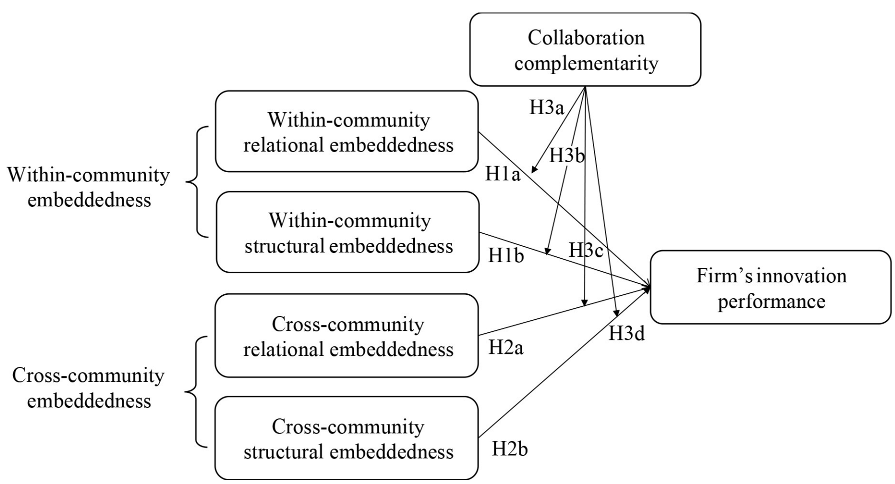

Fig. 1 Conceptual model.

is associated with the connections among members in the same community. A firm with plenty of relationships within the community can access a vast amount of information, knowledge, and other critical resources from fellow community members (Sytch et al., 2012), thereby gaining competitive advantages in innovation resource acquisition. Firms with many within-community connections can also secure resources more swiftly (Rowley et al., 2005). This, in turn, has the potential to accelerate their innovation processes. Additionally, collaborators inside the same community behave similarly, enabling firms to integrate sizable resource advantages into innovation activities at reduced cost and increased speed thereby creating a competitive advantage.

Firms can improve their innovation performance through control benefits generated by within-community structural embeddedness, which refers to the specific position occupied in an innovation community. By connecting disconnected collaborators, firms occupying control positions can compare and contrast the veracity of knowledge provided by the different alternative firms. This can help predict and grasp technology trends and also competitive intelligence (competitors' strategic intentions), which is crucial for innovation development based on their existing knowledge (Han et al., 2020). Firms can also achieve control benefits because they have the necessary access to knowledge and other resources and use their initiative to manage the speed of information flow, which is conducive to innovation performance (Soda et al., 2018). Additionally, intensive connections within the community increase trust and undermine the harness of brokering. Hence, we propose:

Hypothesis 1a: Within-community relational embeddedness has positive impacts on firms' innovation in an ecosystem.

Hypothesis 1b: Within-community structural embeddedness has positive impacts on firms' innovation in an ecosystem.

2.1.2 Cross-community embeddedness

As for cross-community embeddedness, it describes the extent to which a firm is surrounded by firms from different communities. Sparse interactions across diverse communities introduce different "thought worlds," offering a variety of social norms, mentalities, and perspectives. This variety provides a wider range of thoughts, perceptions, and strategies (Pinkse et al., 2018).

Firms can enhance innovation performance through relational embeddedness across communities, indicating connections with members from different communities. Connecting with distinct community members allows a firm to absorb abundant knowledge from collaborators who bring different cultural perspectives and social norms (Wu et al., 2024). Exposure to insights from unfamiliar collaborators can reflect on their own knowledge domain, challenge taken-for-granted views, and broaden the range of alternatives beyond those common to the domain (Ter Wal et al., 2016). This diversity and a broad spectrum of expertise enable them to approach challenges and drive innovation from unique angles.

Cross-community structural embeddedness will also increase the firm's innovation performance. When a firm has high cross-community structural embeddedness, it signifies that the firm holds a dominant position across diverse communities, characterized by well-distributed connections. Acting as a hub among these diverse communities, firms can exert significant influence over how information and resources are transferred (Schilling and Phelps, 2007). This dominance not only amplifies firms' adaptability and resilience in the face of changing market dynamics and technological evolutions (Jiang et al., 2010) but also empowers them to withhold or manipulate resources as needed (Schilling and Fang, 2014). These firms can position themselves as bottlenecks in the innovation process, which ultimately impacts their innovation performance. Meanwhile, establishing connections with a wider range of firms may not be a burden for them, as associated costs decrease over time. Recent studies indicate that actors functioning as hubs are likely to gain increasing opportunities for power and control, leading to lower marginal costs and a positive feedback loop (Clement et al., 2018). Over the long-term, the net benefits of innovation can be favorable. Hence, we propose:

Hypothesis 2a: Cross-community relational embeddedness has positive impacts on firms' innovation in an ecosystem.

Hypothesis 2b: Cross-community structural embeddedness has positive impacts on firms' innovation in an ecosystem.

2.2 The contingent effects of collaboration complementarity

Collaboration complementarity provides an important context to explore the varied relationships between innovation community embeddedness and firms' innovation performances in an ecosystem. Complementarity is an essential feature of system concepts for the study of innovation ecosystems (Jacobides et al., 2018; Reiter et al., 2024; Wang et al., 2024). Based on the degree of complementarity between partners, collaboration in the innovation ecosystem could be divided into complementary collaboration and peer collaboration (D'Ippolito and Ruling, 2019). In complementary collaboration, collaborators bring diverse knowledge and expertise, but learning or transferring such resources also depends on effective communication between the partners. The integration and exploitation of these resources can be costly, potentially outweighing the associated benefits (Jin and Wang, 2021). In contrast, peer collaboration involves partners with similar specializations, which makes it easier to integrate their knowledge, information, and other resources. These collaboration types create two distinct contingencies that affect how the embeddedness influences the innovation of firms. Therefore, in this paper, we focus on the moderating effects brought by collaboration complementarity. Collaboration complementarity is defined as a spectrum that ranges from high complementarity in complementary collaboration to low complementarity in peer collaboration.

Collaboration complementarity plays a positive moderating role in the impact of within-community embeddedness, including relational and structural dimensions, on innovation performance.

As firms engage in complementary collaborations, they can leverage an interplay of diverse resources, fostering synergy and innovation enhancement by offsetting each other's weaknesses (Furlotti and Soda, 2018). In this way, within-community relational embeddedness provides firms with abundant knowledge, information, and other critical resources from complementary domains, such as different links in the industry chain. These resources are valuable in generating new growth opportunities and potential synergies to enhance innovation (Jin and Wang, 2021). Additionally, the shared behavioral patterns among complementors within the same community simplify resource integration into innovation efforts and reduce transaction costs significantly. Meanwhile, firms with high within-community structural embeddedness also gain substantial leverage in brokering complementors, offering a strategic advantage in harnessing collaborative potential. This dominant position not only affords additional learning opportunities but also facilitates collaborative relationships for innovation (Vasudeva et al., 2013). Besides, firms may more easily leverage their brokerage advantages within the community because awareness of shared identities increases trust in each other. With high collaboration complementarity, the innovation benefits generated by within-community relational and structural embeddedness are greatly improved. Hence, we propose:

Hypothesis 3a: The relationship between within-community relational embeddedness and firms' innovation performance is positively moderated by collaboration complementarity.

Hypothesis 3b: The relationship between within-community structural embeddedness and firms' innovation performance is positively moderated by collaboration complementarity.

In contrast, collaboration complementarity plays a negative moderating role in the impact of cross-community embeddedness, including relational and structural dimensions, on innovation performance.

Complementary collaborations, while potentially valuable, generate resources that are often tacit, complex, and challenging to interpret. Learning or transferring such resources requires more costs and effort between the partners (Ennen and Richter, 2010; Jin and Wang, 2021). In this way, cross-community relational embeddedness, while providing firms access to diverse knowledge domains, also demands significant integration efforts. A critical challenge emerges as firms face information overload (Kobarg et al., 2019), struggling to effectively process and synthesize the extensive knowledge flows from unfamiliar and complementary collaborators. This increases the costs of assimilating non-redundant resources (Grigoriou and Rothaermel, 2017), potentially compromising the transformation of these valuable inputs into innovative outputs. Furthermore, firms with high levels of cross-community structural embeddedness encounter substantial risks in effectively controlling a large number of unfamiliar actors. As complementary partners maintain their independent identities, they face moral hazard from the other party, whose behavior is often unobservable and beyond direct control. Competitive motives and monitoring difficulty may convince both partners to withhold their valuable resources when interacting (Jin and Wang, 2021). Consequently, the innovation advantages generated by cross-community relational and structural embeddedness can be diminished. Hence, we propose:

Hypothesis 3c: The relationship between cross-community relational embeddedness and firms' innovation performance is negatively moderated by collaboration complementarity.

Hypothesis 3d: The relationship between cross-community structural embeddedness and firms' innovation performance is negatively moderated by collaboration complementarity.

3 Data and methods

3.1 Data collection

We conduct an empirical study in the global 3D printing industry to test the hypotheses. Over the past 30 years, the industry has rapidly evolved, marked by significant technological breakthroughs (Marić et al., 2023). The complexity and rapid development pace of the 3D printing technology requires collaborative efforts including software, materials science, and precision engineering (Wohlers, International, 2024; Phaal et al., 2024), leading to a higher interdependence among organizations. For instance, developing a specialized 3D-printed medical device involves intricate coordination among material suppliers, printer manufacturers, and healthcare providers (Xu et al., 2022). This interdependence can foster the agglomeration of firms, universities, and organizations, creating a unique environment for exploring innovation communities, unlike traditional manufacturing sectors such as textiles and automotive sector, where R&D activities are often isolated (Zhou et al., 2022). Furthermore, the inherent complexity of 3D printing drives cross-sector collaboration, enabling stakeholders to leverage their strengths, address challenges, and stimulate innovation, while also providing a ground for considering various collaboration orientations. Therefore, it is reasonable to take the global 3D printing industry as an example to explore innovation communities in the ecosystem.

This study employs both patent and business data for empirical analysis, with the data collection process outlined as follows (see Fig. 2). First, we retrieved global patent data related to 3D printing from the Derwent World Patents Index (DWPI) via the Derwent Innovation (DI) search engine. The search query was developed based on references and expert advice, resulting in a total of 90,756 pieces of patent data. Second, we cleaned the data by eliminating invalid data, including duplicates, mergers and acquisitions, and irrelevant branch firms. This yielded 62,466 valid 3D printing-related patents covering 6,109 organizations from 1998 to 2019. These are used to construct the global networks of the 3D printing industry innovation ecosystem. Third, we identified the top 800 firms regarding patent application counts, which were cross-referenced with the OSIRIS database to obtain longitudinal information, including financial and basic firm data. Finally, we identified 161 firms, which are used as the sample for further regression analysis.

3.2 Network construction and community detection

Network construction is based on inter-organizational co-patenting relationships derived from patent data. Since the year of patent publication may not accurately indicate that collaborative relationships between firms only exist in that year, these relationships are likely to persist for several years. Therefore, we constructed the collaboration network of 6,109 organizations using a 5-year window for collaboration, which is consistent with prior studies on patents and innovation (Sytch and Tatarynowicz, 2014; Guan and Liu, 2016). For the collaboration network in year t, it will include inter-organizational co-patenting relationships that occurred in year t−4, year t−3, year t−2, year t−1, and year t. Using 1998–2002 as the first window for which we reconstruct the collaboration network, we produced 16 yearly observations of the evolving collaboration network until 2017.

Following prior literature (Sytch and Tatarynowicz, 2014; Clement et al., 2018; Xu et al., 2020), the topological clustering algorithm is used to identify innovation communities in this study. The method proposed by Louvain is one of the most robust methods of community identification (Clauset et al., 2004). Unlike traditional clustering based on similarities in firms' attribute data, this method can divide a large network into multiple clusters according to the aggregation degree of nodes in the network, which is more effective (Wiedmer and Griffis, 2021). The optimization strategy of the Louvain clustering algorithm is to maximize the modularity Q of the divided network. The larger the Q, the better the division effect. Its definition is as follows (Clauset et al., 2004):

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)^2 \delta(c_i, c_j), \tag{1}$$

where i and j are nodes in the network. m represents the sum of the weights of all connections in the network. A_{ij} represents the weight of the connection between node i and node j. $A_{ij} = 0$ if there is no connection between the two nodes. k_i represents the sum of the weights of connections between node i and other nodes in the

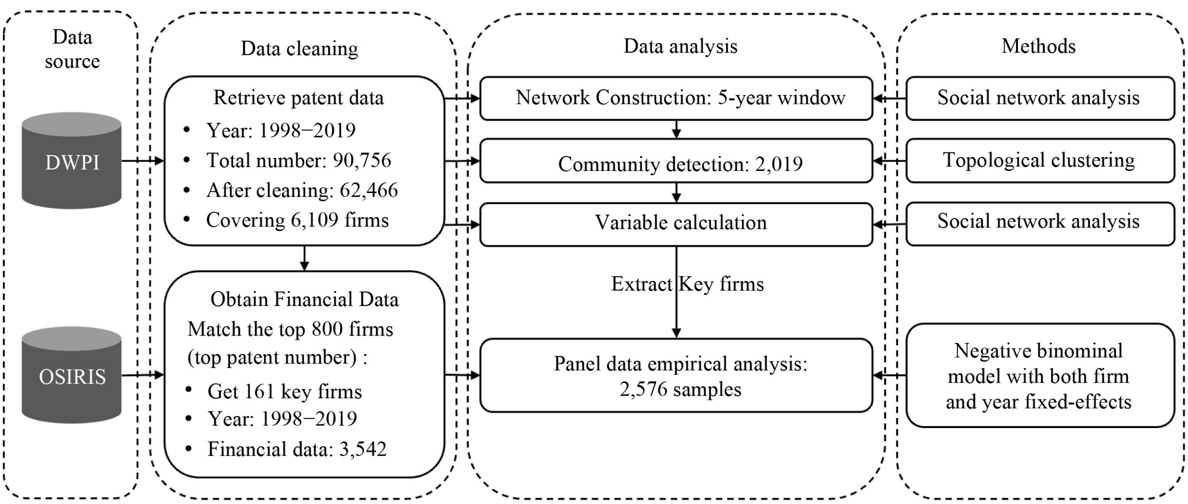

Fig. 2 Data collection and analysis.

network. c_i is the community that node i belongs to. $\delta(c_i, c_j) = 1$ if node i and node j belong to the same community, otherwise $\delta(c_i, c_j) = 0$.

3.3 Variables

3.3.1 Dependent variables

Innovation Performance (IP): We captured the innovation performance of firms using the counts of their patent applications as a proxy (Ahuja, 2000). Patent applications provide an externally validated measure of invention which is why it's considered a proxy though a substantial one. We defined the *Innovation Performance* as the total number of patents that firm i applied for in year t.

3.3.2 Independent variables

Within-community relational embeddedness (RE_{wc}): To test Hypothesis 1a, we defined the *within-community relational embeddedness* of firm i as the total count of ties that connects firm i and other firms within the same community (Gonzalez-Brambila et al., 2013).

Within-community structural embeddedness (SE_{wc}): To test Hypothesis 1b, we defined the *within-community structural embeddedness* of firm i using betweenness centrality as follows (Gilsing et al., 2008):

$$within-community\ structural\ embeddedness_i = \sum_{j=1}\sum_{q=1}\frac{g_{jq}(i)}{g_{iq}}, \tag{2}$$

where firm i, j, q belong to the same community, and $q \neq i, j$. $g_{jq}(i)/g_{jq}$ represents the probability that firm i is on the path of firm j and firm q. Higher values on this index reflect firms that are rich in structural holes.

Cross-community relational embeddedness (RE_{cc}): To test Hypothesis 2a, we defined the *cross-community relational embeddedness* of firms i as the total count of ties that connects firm i and other firms in other innovation communities. The variable is also normalized.

Cross-community structural embeddedness (SE_{cc}): To test Hypothesis 2b, we defined the cross-community structural embeddedness of firm i as:

$$cross-community\ structural\ embeddedness_i = 1-\sum_{s=1}\left(\frac{k_{is}}{k_i}\right)^2, \tag{3}$$

where k_{is} is the number of connections of firm i to firms in community s, and k_i is the total connections of firm i. The variable is therefore close to 1 if its connections are uniformly distributed among all the communities.

Collaboration complementarity ($Comple_{colla}$): To test the moderating effects, we measure collaboration complementarity as patent portfolio similarity analysis using the vector space model (VSM), which was based on natural language processing methods and techniques.

There are several steps in our method. First, 2-*g* and 3-*g* terms were extracted from patent abstracts to build a vocabulary, which defined the dimensions of vector space. Patent abstracts of each firm were mapped into five-year cohorts (from year t−4 to year t) as patent portfolios. Then, we eliminated terms if they appeared in less than 10 of the firms' portfolios, and the rest terms were composed of technical vocabulary.

Second, we generated a weighted vector for each patent portfolio into a single continuous vector space (Younge and Kuhn, 2016), based on the term-frequency inverse-document-frequency (Aizawa, 2003), which is also called "TF-IDF" method.

$$TFIDF(term_A) = \frac{t_A}{T_A} \times \log\frac{D}{D_A}, \tag{4}$$

where t_A is the term frequency of $term_A$ in the target patent portfolio, T_A is the total term frequency of the patent portfolio records that contain the $term_A$, D_A is the number of the patent portfolio records that contain the $term_A$, D is the number of patent portfolio records in the corpus. Technical terms that are more important to a patent portfolio were allocated with higher weights.

Thirdly, the cosine of the angular separation between weighted vectors of two firms was calculated to measure similarity as below:

$$\cos(P_i, P_j) = \frac{\sum_{A=1}^{n} P_{i,A} \times P_{j,A}}{\sqrt{\sum_{A=1}^{n}(P_{i,A})^2} \times \sqrt{\sum_{A=1}^{n}(P_{j,A})^2}}, \tag{5}$$

where $P_{i,A}$ is TF-IDF for $term_A$ in the patent portfolio of firm i, and n is the dimension of the vector space. We have a similarity matrix enumerating every firm-pairs. When the perspective is to reveal the type of collaboration complementarity between firms, integrating collaboration matrix is a must. Coupling with the matrix of interfirm collaboration, the weighted sum of patent portfolio similarity of each firm to other firms was derived as below Eqs. (6) and (7):

$$Similarity_{colla_i} = \sum_{j=1}^{\text{Firms other than } i} \cos(P_i, P_j) \times \frac{Co_{i,j}}{\sum Co_{i,\text{otherfirms}}}, \tag{6}$$

$$Comple_{colla_i} = 1 - Similarity_{colla_i}, \tag{7}$$

where $Co_{i,j}$ is the times firm i cooperates with firm j.

3.3.3 Control variables

To ensure robust results, we controlled for a range of possible determinants of a firm's innovation performance (Sytch and Tatarynowicz, 2014; Zhang et al., 2019). As for the firm level, we controlled for ***Firm size*** (measured as employee number), financial condition (measured as MBIT [***Profits***] and return on assets [***ROA***]), and investments in R&D (measured as research and development expenses divided by operating revenue [***RDI***]). These variables were logged to correct for their distributional skewness. As for the global network level, we controlled for ***Global-network density*** measured as the total number of existing ties among all firms in the network divided by the number of all possible ties among these firms (Knoke and Yang, 2019). As for the community level, we controlled for ***Community size*** as the total number of firms that were members of the firm's innovation community in year *t*, including the focal firm (Sytch and Tatarynowicz, 2014; Clement et al., 2018). All the measurements of variables are also listed in Table 1.

3.4 Model specification

Our dependent variable, innovation performance, is a nonnegative count variable with overdispersion. Therefore, we analyzed the 161 firms by negative binomial regression model with both firm fixed-effects and year fixed-effects (Allison and Waterman, 2002; Aggarwal, 2020) to test the hypotheses - how innovation community embeddedness and collaboration complementarity influence a firm's innovation performance in the ecosystem. To alleviate concerns about outliers driving the results, we winsorized relative variables at the 1st and 99th percentage levels (Yan et al., 2021). We also lagged all independent variables by one year to enable causal interpretation.

$$\begin{aligned} IP_{i,t+1} = \exp\Big(&\beta_0 + \beta_1 RE_{wc_{i,t}} + \beta_2 SE_{wc_{i,t}} + \beta_3 RE_{cc_{i,t}} + \\ &\beta_4 SE_{cc_{i,t}} + \beta_5 Comple_{colla_{i,t}} + \beta_6 RE_{wc_{i,t}} \times \\ &Comple_{colla_{i,t}} + \beta_7 SE_{wc_{i,t}} \times Comple_{colla_{i,t}} + \\ &\beta_8 RE_{cc_{i,t}} \times Comple_{colla_{i,t}} + \beta_9 SE_{cc_{i,t}} \times Comple_{colla_{i,t}} \\ &+ \sum \beta_k Controls_{i,t} + \gamma_{i,t} + \tau_{i,t} + {}_{i,t}\Big). \end{aligned} \tag{8}$$

4 Empirical results

4.1 Network visualization and community identification

Figure 3 illustrates the global inter-organizational

Table 1 Measurements of variables

	Variables	Measurement	Data source	Reference
Dependent variable	*IP*	Patent counts	DPCI	Ahuja (2000)
Independent variables	RE_{wc}	The number of ties that connects firm *i* and other firms in the same community.	DPCI	Gilsing et al. (2008); Gonzalez-Brambila et al. (2013); Wu et al. (2024)
	SE_{wc}	Betweenness centrality of firm *i* within the community.	DPCI	
	RE_{cc}	The number of ties that connect firm *i* and other firms in other communities	DPCI	
	SE_{cc}	The distribution coefficient of ties that connect firm *i* and other firms in other communities.	DPCI	
Moderate variable	$Comple_{colla}$	The patent portfolio similarity of firm *i* using the VSM model.	DPCI	Younge and Kuhn (2016); Whalen (2018);
Control variables	*Firm size*	Employee number	OSIRIS	Sytch and Tatarynowicz (2014); Clement et al. (2018); Zhang et al. (2019)
	Profits	MBIT	OSIRIS	
	ROA	Return on assets	OSIRIS	
	RDI	Research and development expenses divided by operating revenue	OSIRIS	
	Global-network density	The total number of existing ties among all firms in the network divided by the number of all possible ties among these firms	DPCI	
	Community size	The total number of firms that are members of the focal firm's innovation community.	DPCI	

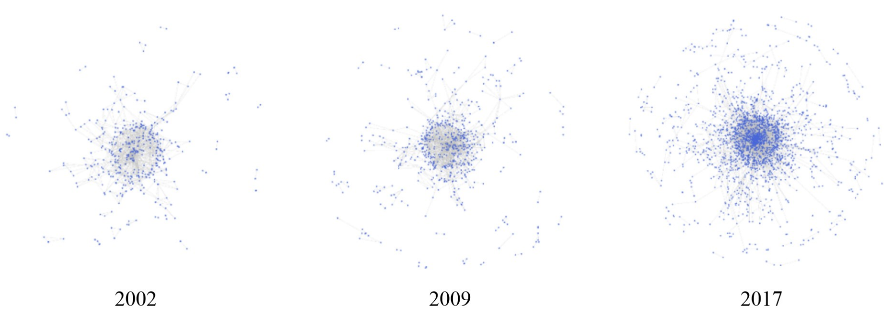

Fig. 3 Illustrations of the global collaboration network in 2002, 2009, and 2017.

networks in 2002, 2009, and 2017. The global networks of the 3D printing industry grew rapidly from 460 firms in 2002 to the maximum size of 2643 firms in 2017. Figure 4 illustrates the identified innovation communities in 2002, 2009, and 2017 separately. The total number of communities in the global collaboration network ranged from 110 in 2002 to 701 in 2017.

4.2 Regression results

Table 2 presents descriptive statistics and correlations between the variables. Table 3 presents the results of our negative binomial models with firm-level and year-level fixed effects. In Table 3, models 1−6 represent the predicted main effects. Model 1 is the baseline model, including only the control variables. Model 2 adds a moderator based on Model 1. Models 3−6 represent the predicted main effects. Models 7−8 represent the predicted moderating effects. Model 9 represents the fully specified regressions containing all predicted effects.

In model 3 and model 4, we test Hypotheses 1a and 1b. Within-community relational embeddedness has positive effects on firms' innovation performance ($\beta = 0.046$, $p < 0.01$), thus supporting Hypothesis 1a. Within-community structural embeddedness also shows positive effects on innovation performance ($\beta = 0.406$, $p < 0.01$), thus supporting Hypothesis 1b. Relational embeddedness can bring more resources and information inside the community to a firm, which may enhance a firm's innovation. Meanwhile, structural embeddedness can bring dominant control benefits of the community to the firm, and thus help improve firms' innovation performance. These findings are also in line with the research examining the connections and structural holes in the ego network, which has shown that firms have better innovation performance with more connections and structural holes (Zaheer and Bell, 2005; Lyu et al., 2019).

In model 5 and model 6, we test Hypotheses 2a and 2b. Cross-community relational embeddedness has positive effects on firms' innovation performance ($\beta = 0.916$, $p < 0.01$), supporting Hypothesis 2a. Hypothesis 2b is also supported, as cross-community structural embeddedness positively affects firms' innovation performance ($\beta = 0.572$, $p < 0.05$). Prior research has proposed that bridging ties between communities provides firms with efficient access to nonredundant information and novel resources, which may increase the innovation potential of the firms (Gulati et al., 2012). Firms also have better innovation performance when they have high cross-community structural embeddedness. It means that a well-distributed control position across the community significantly impacts firms' innovation performance.

In model 7 and model 8, we test Hypothesis 3a to Hypothesis 3d. Model 7 in Table 3 shows collaboration complementarity has significant positive moderating effects on the relationship between within-community relational embeddedness and firms' innovation performance ($\beta = 0.058$, $p < 0.1$), but has insignificant moderating effects on the relationship between within-community structural embeddedness and firms' innovation performance ($\beta = 0.456$, $p > 0.1$). Model 9 shows similar patterns. Thus, we find support for Hypothesis 3a. This indicates that firms' innovation benefits more from within-community connections with higher complementarity. Hypothesis 3b is not supported. Model 8 in Table 3 finds collaboration complementarity has significant negative moderating effects on the relationship between cross-community relational embeddedness and firms' innovation performance ($\beta = -4.057$, $p < 0.05$), and has significant positive moderating effects on the relationship between cross-community structural embeddedness and firms' innovation performance ($\beta = 4.670$, $p < 0.01$). Model 9 shows similar patterns. Thus, we find support for Hypothesis 3c. But hypothesis 3d is not supported. The results are also consistent with Fig. 5. The results demonstrate that the impacts of innovation community embeddedness on innovation performance are contingent on collaboration complementarity. Previous studies suggest that the relationship between network characteristics and innovation performance is mediated by various factors (Song et al., 2017; Rong et al., 2018), which aligns with our findings.

However, we also find that firms benefit more from cross-community structural embeddedness with high complementarity, which contradicts initial hypotheses. A review of related literature (Kwak et al., 2018; Marić et al., 2023) suggests that firms with extensive cross-community structural embeddedness may function as

2002 2009 2017

Fig. 4 Illustrations of the innovation communities in 2002, 2009, and 2017.

Table 2 Descriptive statistics and correlations

	1	2	3	4	5	6
1	1					
2	0.069***	1				
3	0.010	0.358***	1			
4	0.032	0.460***	0.219***	1		
5	0.037*	0.520***	0.805***	0.339***	1	
6	0.226***	0.056***	0.040**	0.092***	0.096***	1
7	−0.024	0.160***	0.022	0.076***	0.034*	0.154***
8	−0.038*	0.068***	0.018	0.014	0.027	−0.310***
9	0.317***	0.054***	−0.012	0.085***	0.028	0.499***
10	0.152***	0.097***	−0.024	0.062***	−0.002	0.064***
11	0.179***	0.054***	0.001	0.048**	0.032	0.266***
12	0.180***	0.074***	0.024	0.075***	0.074***	0.433***
Mean	2.782	7.278	1.030	1.038	1.474	16.732
SD	12.685	4.763	1.086	1.052	1.201	35.734
	7	8	9	10	11	12
7	1					
8	−0.068***	1				
9	0.273***	−0.423***	1			
10	0.158***	−0.276***	0.586***	1		
11	0.207***	−0.173***	0.670***	0.411***	1	
12	0.139***	−0.230***	0.582***	0.333***	0.741***	1
Mean	0.002	0.950	2.248	0.071	0.027	0.042
SD	0.003	0.586	4.194	0.197	0.101	0.118

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

platforms within an ecosystem, enabling them to rapidly capture market needs. Meanwhile, when the collaboration complementarity is high, they engage with actors from other links in the industrial chain, like material companies, software developers, and hardware manufacturers. Once acquiring market information, they can respond by improving material performance, developing advanced software tools, and optimizing printing systems, thus promoting cross-sector innovation. In the 3D printing industry, companies like Hewlett-Packard (HP) exemplify this phenomenon. On the one hand, HP's open-source hardware platform serves as a hub for collaboration among various 3D printer suppliers, such as MakerBot and Cubify, across different fields (Wohlers, International, 2024). On the other hand, HP has forged complementary relationships with a range of partners, including open-source hardware platforms, online service platforms, and low-cost software platforms (Kwak et al., 2018). These complementary relationships enable HP to create a seamless design-to-printing process that enhances efficiency, lowers knowledge barriers for different links, and drives innovation in the 3D printing space.

4.3 Robustness checks

To ensure robust results, we conducted a range of additional tests.

First, we investigated the potential for reverse causality, assessing whether firms with superior innovation performance are able to have higher within-community or cross-community embeddedness. In line with Ning and Guo (2022), we conducted this analysis by using $IP_{i,t+2}$ as the dependent variable, which involves lagging all independent variables by two years. The results for the main effects remain robust (Electronic Supplementary Material Table A Model 1 to Model 4). Additionally, if reverse causality were present, we would expect to see a positive relationship between the dependent and independent variables (Wu et al., 2024). However, our combined analysis of $IP_{i,t+1\ t+2}$ reveals that it does not predict within-community or cross-community embeddedness significantly (Electronic Supplementary Material Table A Model 5 to Model 8).

Second, we explored the sensitivity of our results using other estimation techniques. While we chose a fixed-effects specification to conduct the main analysis and

Table 3 Negative binomial regression models with firm-level and year-level fixed effects

	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9
Firm size (log)	0.031**	0.032**	0.032**	0.028**	0.030**	0.031**	0.028**	0.031**	0.028**
	(2.392)	(2.427)	(2.475)	(2.188)	(2.357)	(2.414)	(2.158)	(2.395)	(2.192)
ROA (log)	0.043	0.043	0.047	0.044	0.043	0.045	0.045	0.051	0.045
	(0.963)	(0.965)	(1.076)	(0.986)	(0.980)	(1.027)	(1.033)	(1.166)	(1.022)
RDI (log)	0.097*	0.096*	0.087*	0.093*	0.091*	0.095*	0.088*	0.087*	0.088*
	(1.931)	(1.909)	(1.742)	(1.854)	(1.814)	(1.896)	(1.757)	(1.743)	(1.768)
Profits (log)	−0.004	−0.003	0.011	0.008	0.003	−0.004	0.017	0.016	0.022
	(−0.080)	(−0.073)	(0.238)	(0.173)	(0.070)	(−0.086)	(0.364)	(0.355)	(0.486)
Community Size	0.002***	0.002**	0.001	0.003***	0.002*	0.002*	0.000	0.001	0.000
	(2.684)	(2.358)	(1.009)	(3.108)	(1.941)	(1.901)	(0.469)	(0.780)	(0.372)
Global Network Density	201.737***	201.604***	183.890***	193.144***	193.917***	200.218***	196.042***	183.963***	193.980***
	(9.625)	(9.616)	(8.712)	(9.129)	(9.178)	(9.546)	(9.021)	(8.606)	(8.878)
$\text{Comple}_{\text{colla}}$ (m)		−0.036	0.078	0.023	−0.018	−0.014	0.019	0.063	0.011
		(−0.621)	(1.253)	(0.368)	(−0.308)	(−0.231)	(0.270)	(0.942)	(0.159)
RE_{wc} (a)			0.046***				0.007	0.044***	0.005
			(6.050)				(0.360)	(4.473)	(0.219)
SE_{wc} (b)				0.406***			−0.221	0.030	−0.251
				(2.756)			(−0.535)	(0.175)	(−0.606)
RE_{cc} (c)					0.916***		−0.213	2.566**	3.228**
					(3.586)		(−0.520)	(1.962)	(2.447)
SE_{cc} (d)						0.572**	0.148	−2.796***	−2.313**
						(2.304)	(0.436)	(−2.579)	(−2.084)
m*a							0.058*		0.065*
							(1.946)		(1.740)
m*b							0.456		0.503
							(0.639)		(0.705)
m*c								−4.057**	−5.398***
								(−2.066)	(−2.652)
m*d								4.670***	3.831**
								(2.954)	(2.336)
_cons	−3.347***	−3.313***	−3.407***	−3.325***	−3.330***	−3.337***	−3.345***	−3.419***	−3.379***
	(−12.400)	(−12.023)	(−12.486)	(−12.148)	(−12.140)	(−12.132)	(−12.159)	(−12.443)	(−12.227)
Firm fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2528	2528	2528	2528	2528	2528	2528	2528	2528
chi2	878.04	877.76	957.12	896.80	893.45	888.04	988.11	977.24	999.33

Notes: The estimates presented in the models are derived from fixed effects negative binomial regression models. *T-value* is in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

control for firm-level and year-level unobservable factors, we also used the random-effects specification (Grigoriou and Rothaermel, 2017), and the results remained robust (Electronic Supplementary Material Table B).

Third we examined whether our results are sensitive to sample truncation. Considering that the maximum-likelihood estimator eliminates all firms with a constant zero outcome, we ran a series of ordinary least squares models to allow for retaining these firms in the estimation (Sytch and Tatarynowicz, 2014). The results of these additional tests were robust (Electronic Supplementary Material Table C).

Fourth, we verified our statistical results using other

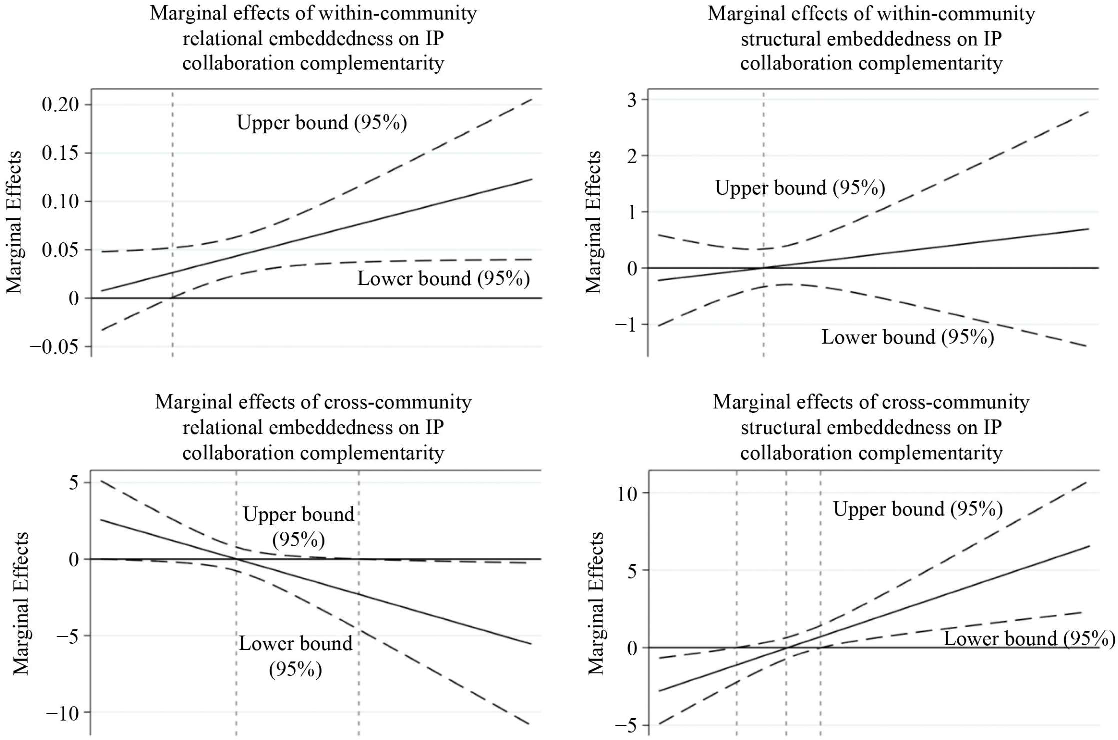

Fig. 5 Marginal effects of innovation performance (Collaboration complementarity as moderate variable).

measurements of the variables. We applied an alternative measurement of SE_{wc} (SE_{wc} = 1 − constraint) (see Electronic Supplementary Material Table D.1). In the step of building technical vocabulary when measuring $Comple_{colla}$, we applied an alternative specification (10%) to eliminate terms (Electronic Supplementary Material Table D.2). The results of additional tests were similar.

Finally, we explored if the results are sensitive to the timeframe of our sample. To address this issue, we divided the sample into two distinct periods and compared the results. Drawing insights from the Wohlers Report (2024), a leading analysis of the 3D printing industry, we noted that global revenue growth in the 3D printing sector was modest until 2009, followed by a significant increase after 2010. Consequently, we defined the two stages of our analysis as 2005–2010 and 2011–2017. The results also show consistent findings (Electronic Supplementary Material Table E).

5 Conclusions

This paper explored how innovation community embeddedness in an ecosystem impacts firms' innovation performance, with the consideration of the contingency effects of collaboration complementarity using the example of the global 3D printing industry. Our research has the following key findings. On the one hand, both within-community relational and structural embeddedness, as well as cross-community relational and structural embeddedness, positively impact firms' innovation performance. On the other hand, collaboration complementarity has contingency effects on the relationships between innovation community characteristics and innovation performance. Firms gain more innovation benefits from within-community relational embeddedness and cross-community structural embeddedness when engaging in complementary collaboration. Conversely, firms with low collaboration complementarity benefit more from cross-community relational embeddedness.

Our research offers several contributions to innovation ecosystem theory. First, by emphasizing the innovation communities in an innovation ecosystem, this research advances the understanding of the relationship between innovation community embeddedness and firms' innovation performance. Previous studies mainly treat the innovation community as a whole, assuming that all firms in the innovation community share equal levels of embeddedness while exploring the effects of these communities on firm performance (Upham et al., 2010; Wang and Yang, 2019; Wang and Lu, 2021; Iurkov et al., 2023). Our findings indicate that organizations exhibit variations in embeddedness—both within and across communities—which lead to differing implications for firms' innovation performance, thereby enhancing our understanding of innovation community embeddedness.

Our second contribution lies in explicating how collaboration orientations help uncover contingent ways in which innovation community embeddedness can influence the firm innovation in an ecosystem, thus fulfilling the research gap that previous research about networks and ecosystems has overlooked the role of collaboration characteristic (Shipilov and Gawer, 2020). Complementarity is a critical element in the innovation ecosystem (Agarwal and Kapoor, 2023; Baldwin et al., 2024). This insight offers a direct contribution to the studies of the innovation ecosystem.

Third, our research contributes to the methodology for studying innovation ecosystems. We construct large-scale collaboration networks and identify innovation communities using the Louvain method (Blondel et al., 2008), demonstrating its effectiveness in analyzing these communities. Additionally, instead of relying on traditional methods like IPC codes to measure complementary collaboration (Makri et al., 2010; Toh and Miller, 2017), we utilize NLP technology for a more nuanced measurement of collaborative complementarity, thereby enhancing future research in this area.

This research has valuable practical implications for both managers and policymakers. First, while policymakers tend to pay attention to the clusters with geographical proximity in an innovation ecosystem, it is also of significance to take notice of innovation communities across regions, particularly in emerging industries. Facilitating the development of innovation communities may accelerate a prosperous innovation ecosystem.

Second, managers aiming for innovation should focus on both internal and external connections. Internally, they should build strong relationships and take on dominant roles within their own innovation communities. Externally, managers should forge partnerships across different communities and spread out their connections to obtain control power. These can help drive new ideas and promote innovation improvements. However, policymakers often understand such ecosystems as qual partnerships without dominant players which contrasts with reality. Any ecosystem member aims at conquering a somewhat dominant position in the ecosystem to maximize its own benefit. Thus, policy interventions aiming at supporting the creation and development of ecosystems need to take this into account and accept that such ecosystems create more advantages for some and fewer advantages for others. However, the overall impact on economies is positive which justifies policy interventions.

Additionally, managers need to consider their firm's collaboration orientation. If a firm prefers working with complementary partners, it's beneficial to strengthen ties within its own community or to position itself as a controller across various communities. Conversely, if a firm often collaborates with peer partners, establishing more connections across different communities is more effective.

Our research is subject to some limitations. The first limitation arises from the specificity of our empirical examination, which focuses on the 3D printing industry. This may raise questions about the generalizability of our findings to other industries. Future research could benefit from extending the examination of innovation communities to a variety of industries, including traditional industries such as automotive manufacturing, as well as emerging sectors like biotechnology. For example, automotive is deeply rooted in large-scale production systems that depend on assembly line optimization. The industry is currently undergoing a digital transformation driven by advancements in digitalization and intelligent technologies, which also fosters the formation of innovation communities. Unlike the 3D printing industry, collaborations within these innovation communities mainly focus on enhancing efficiency through incremental innovation, such as improvements in vehicle components or autonomous driving technologies. These relationships typically involve fewer R&D participants and place a stronger emphasis on regulatory compliance and product reliability. On the other hand, biotechnology is likely to offer another dimension for comparison, a greater emphasis on fundamental research compared to the 3D printing industry. This sector is often marked by groundbreaking technological advancements and intense R&D activity, fostering an environment rich with radical innovation. Innovation communities in this sector are likely to be structured around cutting-edge research collaborations, involving universities, research institutes, startups, and large pharmaceutical corporations. These communities would focus on solving foundational scientific problems, enabling rapid advances in areas such as gene editing or synthetic biology. Exploring how innovation communities are structured and function within these contexts could validate our findings but also enhance our understanding of innovation communities, potentially leading to the development of a more generalized framework.

Second, relying solely on patent data to measure innovation has limitations. While patents are valuable indicators of technological innovation, they also overlook diverse dimensions of creative activity. Not all innovative efforts result in patents, as firms may choose alternative strategies to protect their innovations. Future research should adopt a more holistic and multi-dimensional approach by integrating additional indicators of innovation. For instance, qualitative measures such as industry awards, media recognition, customer adoption rates, employee expertise, and contributions to sustainability initiatives could capture broader innovation dynamics. Combining these with quantifiable metrics, like R&D expenditures, product launches, and firm-level performance indicators, would allow for richer, more comprehensive assessments of innovation. On the other hand, the identification and analysis of innovation communities benefit from the use of multi-source data. Innovation communities are driven by different kinds of practice to share knowledge and spark creative advances. These relationships can span a range of activities, including market interactions, social media engagement, participation in online forums, and contributions to open-source platforms. Moreover, metrics such as the presence of incubators and accelerators, venture capital investments, and startup formation rates can reflect the vitality of these communities. Combining these measures with traditional indicators of innovation would cover not only the outcomes of innovation but also the comprehensive enablers of innovation communities.

Electronic Supplementary Material Supplementary material is available in the online version of this article at https://doi.org/10.1007/s42524-025-4188-x and is accessible for authorized users.

Competing Interests The authors declare that they have no competing interests.

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