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Multi-network embeddedness and innovation performance of R&D employees

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Abstract
Taking the perspective of multi-network embeddedness, this paper constructs the collaboration network of R&D organizations, the collaboration network and knowledge network of R&D employees based on the patent data of 879 R&D employees from 224 R&D organizations, and analyses factors that have significant impacts on R&D employees' innovation performance. The results show that R&D employees' knowledge combinatorial potential and knowledge diversity have significant positive impacts on their innovation performance. R&D employees' degree centralities in the collaboration network mediate the impacts of their knowledge combinatorial potential and knowledge diversity on innovation performance. The degree centralities of R&D organizations moderate the impacts of R&D employees' degree centralities on innovation performance.

Keywords Multi-network embeddedness · Knowledge network · Collaboration network · Innovation performance

Introduction

Researchers have viewed R&D knowledge as an aggregation of knowledge elements used by individuals or organizations for inventive activities (Brennecke & Rank, 2017; Fleming, 2001; Quintana-Garcia & Benavides-Velasco, 2008), and believe that innovation emerges by combining and recombining knowledge elements (Wang et al., 2014; Yayavaram & Ahuja, 2008). A knowledge element is a socially defined category, containing a set of tentative conclusions that the research community of a scientific or technological field holds about facts, theories, methods, and procedures surrounding a subject matter (Wang et al., 2014). Knowledge elements are linked through their joint applications or combinations in innovative activities (Fleming, 2001). Over time, the linkages between knowledge elements form a network that records knowledge elements' combinatorial histories (Carnabuci &

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Bruggeman, 2009). The network is called knowledge network (Guan & Liu, 2016; Wang et al., 2014).

Some empirical studies have taken the perspective of network embeddedness, in which R&D employees are embedded in collaboration networks or knowledge networks. These studies have shown that the innovation activities of individuals are influenced by their collaboration network structure characteristics, such as centralities and structural holes (Peng et al., 2014; Wang et al., 2014; Zhang & Lang, 2013) or knowledge structure characteristics, such as knowledge combinatorial potential and combinatorial opportunities (Brennecke & Rank, 2017; Tang, 2016; Wang et al., 2014).

To date, few studies which take the perspective of network embeddedness have investigated the following areas. First, organization level collaboration networks are seldom taken into account when R&D employees' are embedded in collaboration networks. That is, when studying how collaboration network structure characteristics influence R&D employees' innovation, existing studies mainly focus on employee level collaboration networks. Few of them have included the organization level collaboration networks in their research models. However, the two types of collaboration networks are not independent from each other. According to the multilevel theory, innovation phenomena at one level of analysis are linked to those at another (Gupta et al., 2007). Thus, R&D employees should be embedded in the collaboration networks of both employees and organizations when studying their innovation activities to achieve a complete understanding of collaboration network effects.

Second, few studies have investigated the relationships between the characteristics of R&D employees' knowledge network structure and collaboration network structure. While knowledge networks and collaboration networks may have unique structural features, they are not independent from each other (Brennecke & Rank, 2017). How do R&D employees' knowledge structure characteristics lead to their different positions in the collaboration network? Why can some R&D staff have high degree centralities in the collaboration network? These questions remain under-explored. According to the knowledge-based view, knowledge elements are the main source of R&D investment and innovation output (Grant, 1996). R&D employees' knowledge structure largely determines the dependence of their collaborators on them (Wong et al., 2008). Thus, both knowledge network and collaboration network should be integrated into a research model to attain a full understanding of the impact mechanism of R&D employees' innovation performance.

This research takes the perspective of multi-network embeddedness in which R&D employees are embedded in three types of networks (i.e. the collaboration network of R&D organizations, the collaboration network of R&D employees and the knowledge network) as Fig. 1 presents. In Fig. 1, the blue squares represent R&D organizations, the red circles represent R&D employees, and the hollow circles are symbols of knowledge elements. The concrete lines between organizations or employees indicate collaboration relationships, and the concrete lines between knowledge elements suggest co-occurrence relationships. A dotted line between an organization and an employee reflects that the employee is affiliated with the organization, and a dotted line between an employee and a knowledge element means the employee has the knowledge element. The three networks constitute a complete network space where R&D employees are embedded.

Following some related research (Brennecke & Rank, 2017; Wang et al., 2014), we use knowledge combinatorial potential and knowledge diversity to represent R&D employees' knowledge structure characteristics. Centrality is frequently adopted to reflect nodes' positional characteristics in a network. A node with high centrality has been shown to occupy a valuable position in a network (Wang et al., 2015). In this paper, we also use the variable to represent the network structure characteristics of R&D employees or organizations in the

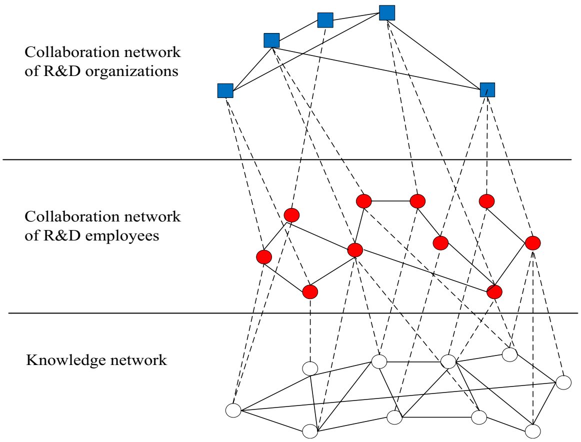


Fig. 1 An illustration of multi-network embeddedness of R&D employees

collaboration networks. We aim to answer the following questions: How do R&D employees' knowledge structure and collaboration network structure characteristics influence their innovation performance? How does the interaction of the two types of collaboration networks influence R&D employees' innovation performance? How do R&D employees' knowledge structure characteristics influence their positions in the employee collaboration network?

Theoretical background and hypotheses

R&D employees' knowledge combinatorial potential and innovation performance

An R&D employee's knowledge combinatorial potential refers to the suitability for combining his or her knowledge elements with those of other R&D employees (Brennecke & Rank, 2017). It is derived from the position of his or her knowledge elements within the knowledge network. In another word, an R&D employee's knowledge combinatorial potential can be reflected by the combinatorial potential of his or her knowledge elements. The combinatorial potential of a knowledge element is indicated by its degree centrality in the knowledge network (Wang et al., 2014). The high degree centrality of a knowledge element indicates it has been combined with many other knowledge elements in the past and has high combinatorial potential in the future (Guan & Liu, 2016; Zhang & Luo, 2020). The combinatorial potential of an R&D employee can be viewed as the sum of the combinatorial potential of all his or her knowledge elements (Brennecke & Rank, 2017). An R&D employee with high knowledge combinatorial potential has more opportunities to cooperate with other employees because his or her knowledge elements have a larger combination range. Such an advantage enables the employee to acquire heterogeneous information or knowledge conducive to innovation and to explore the possibilities of new knowledge combinations (Yayavaram & Ahuja, 2008). In addition, more exchanges with other R&D staff enable the focal employee to better exploit existing knowledge elements for combination, reduce the uncertainty of innovation, and further promote the efficiency and effectiveness of innovation (Fleming, 2001). Therefore, we propose:

H1 An R&D employee's knowledge combinatorial potential has a positive effect on his/her innovation performance.

R&D employees' knowledge diversity and innovation performance

Knowledge diversity refers to the variety in knowledge elements possessed by an R&D employee when embedded in a knowledge network (Brennecke & Rank, 2017). Some R&D employees may hold a large set of knowledge elements which is distributed among different areas, while others may be connected to only a few knowledge elements in the knowledge network. Knowledge diversity is related with knowledge heterogeneity which facilitates new combinations and enhances the likelihood of developing new ideas (Cuervo-Cazurra et al., 2018; Rodan & Galunic, 2004). In another word, knowledge diversity can affect R&D employees' abilities to innovate by recombining knowledge elements (Carnabuci & Operti, 2013). On the one hand, diverse knowledge facilitates the innovative process by enabling R&D employees to make various associations and linkages among knowledge elements. Various knowledge elements increase the probability that R&D employees solve a given technological problem by a novel approach (Ahuja & Katila, 2001). On the other hand, the knowledge diversity of an R&D employee affects his or her opportunities to collaborate with others through knowledge combination. R&D employees with various knowledge elements have more communication and interaction with their colleagues because they can provide complementary knowledge elements for others (Melero & Palomeras, 2015). This is conducive for them to obtain new ways to combine knowledge elements during the communication and interaction process and improve the level of innovation (Cuervo-Cazurra et al., 2018). Therefore, we propose:

H2 An R&D employee's knowledge diversity has a positive effect on his/her innovation performance.

The mediation effect of R&D employees' degree centralities

The degree centrality of an R&D employee refers to the number of direct ties he or she has in the collaboration network. It denotes the extent to which the employee occupies a strategic position (Gnyawali & Madhavan, 2001; Wang et al., 2015). The high degree centrality of an R&D employee indicates that he or she has established many collaboration ties with other employees. An R&D employee's knowledge combinatorial potential is based on the strength of other employees' belief in the feasibility and desirability of combining their knowledge elements with those of his or hers (Wang et al., 2014). High knowledge combinatorial potential offers an R&D employee a good foundation to collaborate with other inventors through knowledge combination, which leads him or her to be frequently chosen as collaborators. On the contrary, the low knowledge combinatorial potential of an R&D employee suggests low levels of inventors' belief in the value of the knowledge element he or she has (Yayavaram & Ahuja, 2008). It may also indicate that the employee has little experience in combining the element with others (Brennecke & Rank, 2017). As a result, there is not a good chance that he or she establishes many ties in the collaboration network. Therefore, we propose:

H3 An R&D employee's knowledge combinatorial potential has a positive effect on his/her degree centrality in the collaboration network.

R&D employees with diverse knowledge hold a large set of knowledge elements which distribute among different areas. The large knowledge base can increase the possibility that their knowledge structure is complementary to that of other inventors. Compared to those with narrow knowledge, they are more likely to provide their collaborators with heterogeneous knowledge elements which facilitate new knowledge combinations and enhance the likelihood of developing new ideas (Cuervo-Cazurra et al., 2018; Rodan & Galunic, 2004). Their broad knowledge may also make it easier for other inventors to find a common knowledge base for cooperation (Melero & Palomeras, 2015). In addition, they are better able to relate knowledge from different areas and make more informed choices with respect to knowledge recombination, which enables them to suggest a new angle on a given problem and make them popular sources for collaboration from the perspective of their colleagues (Brennecke & Rank, 2017; Gruber et al., 2013). Therefore, we propose:

H4 An R&D employee's knowledge diversity has a positive effect on his/her degree centrality in the collaboration network.

An R&D employee who is central in the collaboration network can exert more influence by virtue of being linked with a large number of nodes in the network. He or she is more likely to be connected with other powerful inventors, potentially receiving information of high quantity and quality (Ahuja et al., 2003). A central position in the collaboration network enables an R&D employee not only to capture information and take informed risks in exploring new ideas but also to utilize potential resources and seize new opportunities (Gulati, 2008; Wang et al., 2014). In addition, other inventors are more willing to exchange with the central inventor because of his/her credibility (Reinholt et al., 2011; Wang et al., 2015). This prominence enables a centrally positioned R&D employee to receive additional information on how to combine knowledge elements. In a word, the favorable position can lead to the improvement of the R&D employee's innovation performance.

As mentioned above, an R&D employee's degree centrality can influence his or her innovation performance. Meanwhile, both knowledge combinatorial potential and knowledge diversity of an R&D employee could positively influence his/her degree centrality. Therefore, we propose that an R&D employee's knowledge structure has positive indirect effects on his/her innovation performance through his/her degree centrality.

H5 An R&D employee's degree centrality in the collaboration network mediates the effect of his/her knowledge combinatorial potential on his/her innovation performance.

H6 An R&D employee's degree centrality in the collaboration network mediates the effect of his/her knowledge diversity on his/her innovation performance.

The moderating effect of R&D organizations' degree centralities

When R&D employees are embedded in collaboration networks, according to the multilevel theory, their innovation activities are not only related to their positions in the employee collaboration network but also related to the environment (i.e. the organization collaboration network) they are embedded in (Gupta et al., 2007). That is, the interaction of the two types of collaboration networks can influence R&D employees' innovation (Zhang & Tan, 2014). Organizations with high degree centralities can get more information or knowledge from the collaboration network, which contributes to their knowledge stocks (Mason & Watts, 2012). As a result, R&D employees affiliated with centrally positioned organizations are more likely to obtain diverse knowledge elements from within the organizations, which benefit their innovation activities through knowledge combination. In addition, knowledge diversity makes them popular collaborators. They can obtain heterogeneous knowledge elements when collaborating with other inventors. Consequently, high innovation performance can be expected. Therefore, we propose:

H7 An R&D organization's degree centrality positively moderates the effect of its R&D employees' degree centralities on their innovation performance.

Figure 2 presents the research model.

Methodology

Sample and data collection

This study takes the patent data in the field of nano energy as an example to test the hypotheses. Nano energy can be widely used in industries such as environmental protection, digital diagnosis and treatment, vehicle networking, biomedicine, Internet of Things, etc. Given the great commercial value and promising prospect of nano energy, it is of great practical significance to clarify the mechanism of innovation in the field. In addition, this field is characterized by fast knowledge growth, diverse knowledge, high science linkages, and the formation of extensive collaboration networks. Therefore, innovative activities in the area of nano energy seem to be appropriate objects for the study of multi-network embeddedness. Following the searching strategy used by Guan and Liu (2016), we collected patent data related to nano energy between 2011 and 2018 from the Derwent Innovation Index database. 14,100 results were found.

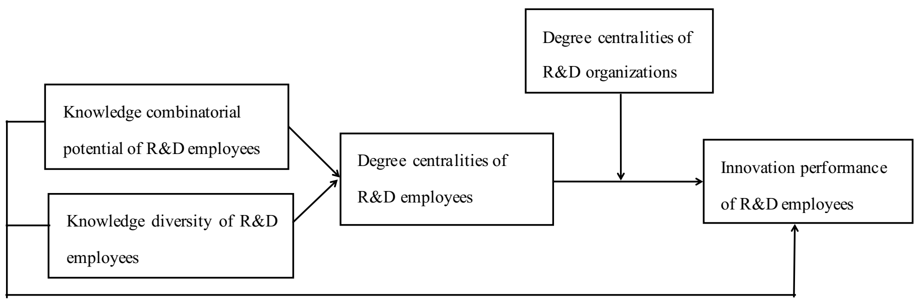


Fig. 2 Research model

Measurement

Like previous studies (Brennecke & Rank, 2017; Guan & Liu, 2015), we use the International Patent Classification (IPC) system to approximate knowledge elements. The IPC code is a hierarchical classification system that consists of sections, classes, subclasses, main groups, and sub-groups. Many previous studies suggest that subclass-level IPC codes (the first four digits in IPC codes) can sufficiently express technological features (Brennecke & Rank, 2017; Guan & Liu, 2015; Park & Yoon, 2014), so we also use 4-digit IPC codes to denote knowledge elements. Previous research suggests that collaboration ties could last for three to five years (Tong et al., 2008). Given the fast development in the field of nano energy, in this paper, we use a three-year rolling window (2011–2013, 2012–2014, 2013–2015……2016–2018) to study the innovation activities of R&D employees. R&D employees' knowledge combinatorial potential and knowledge diversity in Period t are computed based on the data from 2011 to the last year of the period. The degree centralities of both R&D employees and organizations are calculated based on the collaboration networks in Period t. For example, R&D employees' knowledge combinatorial potential and knowledge diversity in Period 2013–2015 are computed based on their knowledge elements from 2011 to 2015. R&D employees' degree centralities and organizations' degree centralities are computed based on their patent co-application activities in 2013–2015. To alleviate the potential reverse causality, following some previous research (Wang et al., 2014; Yan & Guan, 2018), we use a 3-year time lag between the independent and dependent variables. That is, R&D employees' innovation performance in Period 2011–2013, 2012–2014, 2013–2015 is calculated by the patent data collected in Period 2014–2016, 2015–2017, 2016–2018, respectively. The knowledge network, R&D employee collaboration network and R&D organization collaboration network are constructed in each observation period to compute the variables. Taking Period 2013–2015 as an example, Fig. 3 presents the organization collaboration network. If two organizations co-apply for a patent in the period, a tie is established between them. Like some prior studies (Guan & Liu, 2016; Wang

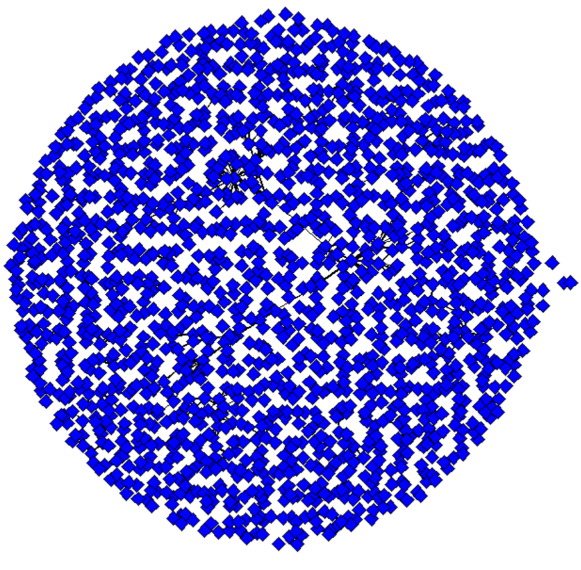


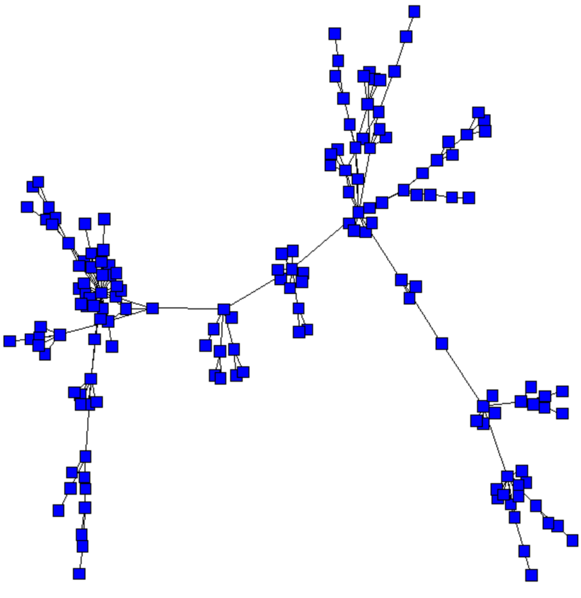
Fig. 3 Organization collaborion network of Period 2013–2015

et al., 2014; Yan & Guan, 2018), we only consider whether two organizations have established a collaboration relationship without discussing the frequencies of their collaboration. That is, the links in the network are not weighted.

As Fig. 3 shows, there are many isolated nodes in the network. The degree centrality of each isolated organization is zero. As including a large number of zeros may lead to a severely skewed distribution of variables and cause a significant bias in model estimation (Li et al., 2013), we only target the organizations in the largest connected subgraph in the network (Fig. 4). In Fig. 3, there are 1701 organizations in total. The largest connected subgraph contains 159 organizations, which are our sample candidates. Furthermore, we only consider the organizations and their employees that are active in patent applications in observation period pairs (e.g. 2013–2015 and 2016–2018) to avoid many zeros in variable values. We also only keep the R&D employees who are affiliated with only one organization. Those who have collaborated with two or more organizations are dropped from the sample data for the following reasons: first, one aim of this research is to test the moderating effect of an organization's degree centrality on the relationship between its employees' degree centralities and innovation performance, so we need to focus on the one-to-one relationship between an organization and an R&D employee. Those who work for more than one organization do not fall into this category. Second, although the mobility of inventors from one company to another could affect knowledge flows and the configuration of collaboration networks (Wouden and Rigby, 2021), these effects are already reflected by R&D employees' knowledge structure characteristics and network structure characteristics. Thus, it's not necessary to analyze those employees in particular. As a result, 68 organizations and 464 R&D employees are selected as samples in Period 2013–2015.

Based on the data collection method, we finally derive 1213 employee-period observations between 2011 and 2018. The number of employees involved is 879, and the number of organizations with which employees are affiliated is 224. Thus, the panel data we collect is unbalanced.

Fig. 4 The largest connected subgraph in organization collaboration network of Period 2013–2015



Independent variables

Knowledge combinatorial potential of R&D employees The knowledge combinatorial potential of an R&D employee is measured by the sum of the combinatorial potential of all his/her knowledge elements (Brennecke & Rank, 2017). The combinatorial potential of a knowledge element is reflected by its degree centrality in the knowledge network (Wang et al., 2014). As an example, Fig. 5 presents the knowledge network of Period 2011–2013, where the 4-digit codes near the nodes are the IPC codes (i.e. the names of knowledge elements). If two knowledge elements co-occur in a patent, a tie is formed between them. The greater the degree centrality, the higher the combinatorial potential.

Knowledge diversity of R&D employees Knowledge diversity refers to the extent to which an R&D employee's knowledge is dispersed across different technological areas (Carnabuci & Operti, 2013). Thus, it should be reflected by both the number and the distribution of the employee's knowledge elements (Stirling, 2007). In this paper, we use the Simpson Diversity Index to measure the variable, which indicates a combination of variety and balance of knowledge categories (Rafols & Meyer, 2010).

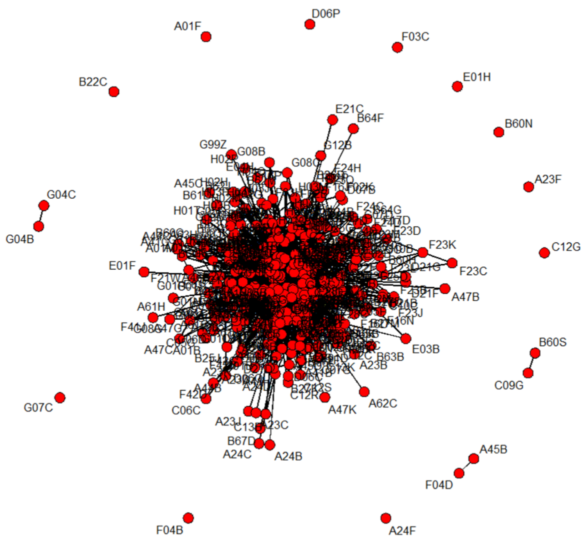
$$\text{knowledge diversity} = 1 - \Sigma_i \left(\frac{n_i}{n_p} \right)^2 \tag{1}$$

where n_i is the frequency of knowledge elements i, n_p is the total number of patents the employee has.

Dependent variable

The number of patents has been adopted as a proxy for innovation performance in many previous studies (Chuluun et al., 2017; Fischer & Leidinger, 2014; Yan & Guan, 2018). Therefore, we also use the number of patents an R&D employee applies for in the observation period to measure his/her innovation performance.

Fig. 5 Knowledge network of Period 2011–2013



Mediating variable and moderating variable

In this paper, the degree centrality of an R&D employee is used as the mediator. The degree centrality of an R&D employee is measured by the number of direct ties he or she has in the collaboration network of R&D employees. The larger the number of direct ties, the greater the employee's degree centrality. It needs to be pointed out that the degree centrality of an R&D employee is calculated based on the number of all his/her collaboration ties, not limited to the ties with the employees from the sample organizations. The degree centrality of an R&D organization (i.e. the moderator) is measured by the number of direct ties it has in the collaboration network of R&D organizations.

Control variables

In addition to the variables which reflect R&D employees' knowledge structure characteristics and network structure characteristics, some other factors may also affect the their innovation performance. Therefore, we introduce some control variables, namely, organization type and R&D employees' R&D capacity. The propensities to apply for patents may vary among different organizations (Guan & Liu, 2016). There are three types of organizations in this research (i.e. university, institute, firm). Thus, we include two dummy variables to indicate an organization is a university, an institute or a firm (the default is firm). R&D employees' innovation performance is also affected by their R&D capacity. An employee's R&D capacity can be viewed as his/her ability to make use of extant knowledge elements to yield innovation outcomes. To control for this possible effect, we use the quotient of the number of patents and the number of knowledge elements of an R&D employee has to reflect his/her R&D capacity (Zhang & Luo, 2020).

Analysis and results

Data analysis

The descriptive statistics and correlation matrix of the variables are presented in Table 1. The highest Variance Inflation Factor (VIF) of all independent variables is 3.153, which is less than the common threshold of 5.0. Therefore, multicollinearity is not problematic.

The likelihood-based estimation approach and the generalized estimating equation (GEE) based approach are the two main-stream approaches for longitudinal data analysis (Fang et al., 2019). The GEE approach has some appealing properties for estimating longitudinal data. On the one hand, in many longitudinal designs the GEE estimator is almost as precise or efficient as the Maximum Likelihood Estimation (MLE). On the other hand, the GEE approach can readily handle imbalance in the response variables (Fitzmaurice et al., 2011). Given the data we collect is unbalanced panel data and the dependent variables are non-negative integers, we adopt the counting models in GEE to test the hypotheses. Table 2 presents the results.

As Model 4 in Table 2 shows, R&D employees' knowledge combinatorial potential has a positive effect on their innovation performance ($\beta = 0.430$, $p < 0.001$), Hypothesis 1 is supported. The coefficient of R&D employees' knowledge diversity is positive and significant ($\beta = 0.484$, $p < 0.001$), confirming Hypothesis 2. According to Model 2, the corresponding

Table 1 Descriptive statistics and correlation matrix

	1	2	3	4	5	6	7	8
1 Innovation performance of R&D employees	1							
2 Knowledge diversity of R&D employees	.301**	1						
3 Knowledge combinatorial potential of R&D employees	.668**	.628**	1					
4 Degree centralities of R&D employees	.760**	.351**	.694**	1				
5 Degree centralities of R&D organizations	−.163**	−.067*	−.105**	.060*	1			
6 University	.121**	.034	.118**	.006	−.237**			
7 Institute	.063*	−.010	.011	.016	−.292**	−.194**		
8 R&D capability of employees	.220**	−.495**	−.036	.179**	−.053	.083**	.026	1
Mean	5.189	0.6787	742.621	21.579	6.667	0.159	0.166	0.681
Std	8.941	0.284	616.62	22.814	5.627	0.367	0.372	0.394

*$p < 0.05$; **$p < 0.01$

Table 2 Results of GEE

Variable	Degree centrality of R&D employees		Innovation performance of R&D employees			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	3.075***	2.940***	1.485***	1.197***	1.204***	1.201***
R&D capability of employees	0.156***	0.208***	0.245***	0.320***	0.250***	0.243***
Institute	0.024	−0.070***	0.363***	0.203***	0.198***	0.105**
University	−0.012	−0.210***	0.478***	0.195***	0.268***	0.196***
Knowledge combinatorial potential of R&D employees		0.352***		0.430***	0.269***	0.258***
Knowledge diversity of R&D employees		0.267***		0.484***	0.460***	0.432***
Degree centralities of R&D employees					0.169***	0.216***
Degree centralities of R&D organizations						−0.178***
Degree centralities of R&D employees × Degree centralities of R&D organizations						0.064***
Wald chi^2	944.44	11,669.00	1110.85	6298.58	7367.61	7266.37
p value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

coefficients of R&D employees' knowledge combinatorial potential and knowledge diversity are positive and significant ($\beta = 0.352$, $p < 0.001$, $\beta = 0.267$, $p < 0.001$, respectively), indicating that R&D employees' knowledge combinatorial potential and knowledge diversity can positively affect their degree centralities in the employee collaboration network. Therefore, Hypothesis 3 and Hypothesis 4 are supported.

To test the mediating effect of R&D employees' degree centralities, we regress R&D employees' innovation performance on their knowledge combinatorial potential, knowledge diversity and degree centralities. Results from Models 5 show that the coefficients of knowledge combinatorial potential and knowledge diversity are reduced in comparison with those in Model 4, though the effects remain significant, which means R&D employees' degree centralities partly mediate the relationship between their knowledge combinatorial potential (or knowledge diversity) and innovation performance. Thus, Hypothesis 5 and Hypothesis 6 are supported.

To test the moderating effect of R&D organizations' degree centralities, we introduce the product of R&D employees' degree centralities and R&D organizations' degree centralities into the regression equation. As Model 6 shows, the coefficient of the interactive item is significant ($\beta = 0.064$, $p < 0.001$), indicating that R&D organizations' degree centralities can moderate the effect of R&D employees' degree centralities on their innovation performance. Therefore, Hypothesis 7 is supported.

Robust check

To check the robustness of the findings, we adopt a new proxy for R&D employees' innovation performance. Specifically, we measure the dependent variable by R&D employees' new knowledge elements in the observation period (Wang et al., 2014). New knowledge elements are those which appear in R&D employees' knowledge stocks in the observation period but do not occur in the previous periods. The hypotheses are also tested by GEE. Table 3 presents the results. As Table 3 shows, the results are consistent with the previous results. Thus, our findings are robust.

Table 3 Robust check results

	Model 1	Model 2	Model 3	Model 4
Constant	1.485***	1.382***	1.376***	1.381***
R&D capability of employees	0.174***	0.267***	0.228***	0.221***
Institute	0.153***	0.078*	0.073*	0.000
University	0.300***	0.144***	0.195***	0.137***
Knowledge combinatorial potential of R&D employees		0.234***	0.099**	0.092***
Knowledge diversity of R&D employees		0.332***	0.329***	0.312***
Degree centralities of R&D employees			0.147***	0.177***
Degree centralities of R&D organizations				−0.121***
Degree centralities of R&D employees × Degree centralities of R&D organizations				0.044***
Wald chi^2	365.32	1917.36	2278.73	2282.64
p value	0.0000	0.0000	0.0000	0.0000

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Regarding the endogenous issue in regressions, we use a Hausman test to verify the endogeneity of the explanatory variables (Guan et al., 2015). Referring to the work of Guan et al. (2015), we introduce two instrumental variables, namely, the density of knowledge network and the number of knowledge elements in the knowledge network. The density of knowledge network reflects the extent to which knowledge elements link to each other, so it is relevant to the combinatorial potential of knowledge elements. According to the definition of an R&D employee's combinatorial potential, the knowledge network density is related with the combinatorial potential of an R&D employee but unlikely to be correlated with his or her patent output. Similarly, the number of knowledge elements in the knowledge network is relevant to an R&D employee's knowledge diversity but not directly related with his or her innovation performance. Thus, the two variables can be regarded as appropriate instruments. We first run the regression model with instrumental variables under fixed effects, then run the model with no instruments under fixed effects. After that, we run a Hausman test to compare the regression results. The small chi-square value and large *p* value ($\chi^2 = 0.33$, $p > 0.1$) indicate that the instrument approach is not necessary. That is, the endogeneity of the explanatory variables is not problematic.

Discussion and conclusions

This paper embeds R&D employees in the collaboration network and knowledge network of R&D employees and the collaboration network of R&D organizations to study how the structural characteristics of the three types of networks influence their innovation performance. To the best of our knowledge, this is one of the first studies which takes the perspective of multi-network embeddedness to explore the influence factors and impact paths of R&D employees' innovation performance. Thus, our research provides a new perspective to study R&D employees' innovative activities. The findings of our study may advance theoretical research and inform practice.

Theoretic contributions

First, we include organization collaboration network in our research model and reveal that R&D employees' innovation performance is not only influenced by their degree centralities in the employee collaboration network but also moderated by the degree centralities of their organizations in the organization collaboration network. While some previous studies have embedded R&D employees in knowledge networks and collaboration networks (Brennecke & Rank, 2017; Wang et al., 2014), few of them have considered multilevel collaboration networks. In another word, organization level collaboration network has not been taken into account in most existing research. Our research contributes to literature which takes the perspective of network embeddedness to study innovation by demonstrating that the interaction of the collaboration networks on two levels has a significant effect on R&D employees' innovation performance, which can be viewed as a confirmation of the multilevel theory. Thus, when studying R&D employees' behavior through network embeddedness, the organization level network should be considered an important factor.

Second, we reveal that R&D employees' network structure characteristics play a mediating role between their knowledge structure characteristics and innovation performance. On the one hand, R&D employees' knowledge structure characteristics can directly influence their innovation performance. Specifically, R&D employees with high knowledge combinatorial potential or knowledge diversity are more likely to achieve high innovation performance. On the other hand, R&D employees' knowledge structure characteristics can affect their innovation performance through their degree centralities in the collaboration network. To the best of our knowledge, there are only a few studies which have integrated knowledge networks and collaboration networks into a single analytical framework to study factors influencing innovation activities (Guan & Liu, 2016; Wang et al., 2014). However, they only test the separate influence of the two networks on innovation outcomes. This research extends related research by linking the three concepts together. Thus, our study complements the understanding of the mechanism by which R&D employees' knowledge structure characteristics affect innovation performance.

Third, this study shows how and why some R&D employees can occupy central positions in the collaboration network from the perspective of their knowledge structure characteristics. We find that R&D employees' knowledge combinatorial potential and knowledge diversity can positively influence their degree centralities in the collaboration network. That is, R&D employees' knowledge structure characteristics play a critical role when they try to establish collaborative relationships with other inventors. Those with high knowledge combinatorial potential and knowledge diversity are more likely to create ties with other employees in the collaboration network. Though Brennecke and Rank (2017) have studied the relationship between inventors' knowledge structure characteristics and their network structure characteristics which are reflected by advice-seeking behaviors within the firm, advice-seeking is considered informal interaction between inventors. The collaboration network in this paper is constructed on the basis of R&D employees' patent application cooperation, which can be regarded as formal interaction between R&D employees both within and across organizations. Therefore, our study can be viewed as a complement to the research on the relationship between R&D employees' knowledge structure and network structure.

Practical implications

First, since knowledge combinatorial potential and knowledge diversity can positively affect innovation performance, R&D employees should attach importance to the development of knowledge elements which have high degree centralities in the knowledge network. On the one hand, these knowledge elements are conducive to enhancing R&D employees' knowledge combinatorial potential, which has a positive effect on their innovation performance. On the other hand, these elements also contribute to R&D employees' knowledge diversity, which could further enhance their innovation performance. Second, given the mediating role of the degree centralities in the collaboration network, R&D employees should try to establish more collaboration relationships with their colleagues so as to optimize their knowledge structure and increase their degree centralities in the collaboration network, which can benefit their innovation performance. Third, based on the moderating effect of organizations' degree centralities, R&D employees may consider joining centrally positioned organizations, from which they may obtain more knowledge elements and strengthen the effect of their network positions on innovation performance.

Limitations and future research

This study has some limitations. First, we examine the hypotheses based on the patent data in the field of nano energy, which may not be generalized to other fields. Future research could generalize the findings using other data or multiple data sources to enhance validity. Second, in this research, R&D employees' innovation performance is measured in terms of their patent applications or knowledge elements, which may not be applicable to some innovation fields. Future research may adopt some other variables (e.g. new product development or improvement) as proxies for innovation performance.

Future studies may also advance our understanding by using some other variables to represent R&D employees' knowledge structure or network structure. For example, knowledge similarity or knowledge uniqueness could be regarded as proxies for R&D employees' knowledge structure characteristics. Pertaining to network structure, some other types of centralities (e.g. closeness centrality, betweenness centrality), cluster coefficient, or ego-network density could also be considered.

Regarding the research model, we focus on the effect of R&D employees' knowledge structure characteristics on their collaboration network structure in this study. Since R&D employees' connections can be a source of new knowledge, it is also possible that R&D employees' positions in the collaboration network can affect their knowledge structure. In addition, inter-organizational connections may also be influenced by inter-personal collaborations. Future research may test these relationships.

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