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KNOWLEDGE NETWORKS AND AMBIDEXTROUS LEARNING: WHAT IS THE IMPACT ON INNOVATION PERFORMANCE?

Rede de conhecimento e aprendizagem ambidestra: qual é o impacto no desempenho da inovação?

Redes de conocimiento y aprendizaje ambidiestro: ¿cuál es el impacto en el rendimiento de la innovación?

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ABSTRACT

Knowledge networks have become a critical factor in the development of innovation. However, most studies focus on the innovation benefits derived from network embedding, and there are fewer studies on firms' knowledge networks from the perspective of feature attributes. This study analyzes the direct and interactive effects of knowledge diversity and the combination of knowledge potential on innovation performance. The research also explores how the complementarity of ambidextrous learning affects the relationship between knowledge networks and innovation performance. The empirical analysis is based on panel data from 116 firms in China's automotive manufacturing industry from 2010-2018. The results processed by the fixed effects negative binomial regression model indicate that the combinatorial potential of knowledge has an inverted U-shaped relationship with firm innovation performance, and knowledge diversity has a positive effect on firm innovation performance. There is an interactive effect between knowledge combination potential and knowledge diversity, and their mutual coordination improves firm innovation performance. The complementarity of ambidextrous learning significantly and positively moderates the positive relationship between the combination potential of knowledge and firm innovation performance.

Keywords: knowledge networks, the complementarity of ambidextrous learning, combination potential of knowledge, knowledge diversity, automotive manufacturing.

RESUMO

A rede de conhecimento tornou-se um fator crítico para o desenvolvimento da inovação. No entanto, a maioria dos estudos têm se concentrado nos benefícios da inovação derivados da incorporação de redes, mas há menos estudos sobre a rede de conhecimento da empresa do ponto de vista dos atributos de características. Este estudo visa analisar os efeitos diretos e interativos da diversidade de conhecimento e do potencial combinatório de conhecimento no desempenho da inovação, e como a complementaridade da aprendizagem ambidestra afeta a relação entre as redes de conhecimento e o desempenho da inovação. A análise empírica baseia-se em dados de painel de 116 empresas da indústria automobilística da China de 2010 a 2018. Os resultados processados pelo modelo de regressão binomial negativa de efeitos fixos indicam que o potencial combinatório de conhecimento tem uma relação invertida em forma de U com o desempenho da inovação empresarial, e a diversidade de conhecimento tem um efeito positivo no desempenho dessa inovação. Existe um efeito interativo entre o potencial combinatório do conhecimento e sua diversidade, sendo que a coordenação entre eles melhora o desempenho das empresas em matéria de inovação. A complementaridade da aprendizagem ambidestra modera positivamente e de maneira significativa a relação positiva entre o potencial combinatório de conhecimento e o desempenho da inovação empresarial.

Palavras-chave: *rede de conhecimento, complementaridade da aprendizagem ambidestra, potencial combinatório de conhecimento, diversidade de conhecimento, fabricação automotiva.*

RESUMEN

Las redes de conocimiento se han convertido en un factor crítico en el desarrollo de la innovación. Sin embargo, la mayoría de los estudios se han centrado en los beneficios de la innovación derivados de la incorporación de redes, pero hay menos estudios sobre las redes de conocimiento de las empresas desde la perspectiva de los atributos de las características. Este estudio analiza los efectos directos e interactivos de la diversidad del conocimiento y el potencial de la combinación de conocimientos sobre el rendimiento de la innovación, y cómo la complementariedad del aprendizaje ambidiestro afecta a la relación entre las redes de conocimiento y el rendimiento de la innovación. El análisis empírico se basa en datos de panel de 116 empresas de la industria automotriz de China entre 2010 y 2018. Los resultados procesados por el modelo de regresión binomial negativa de efectos fijos indican que el potencial combinatorio del conocimiento tiene una relación en forma de U invertida con el rendimiento de la innovación de las empresas, y la diversidad del conocimiento tiene un efecto positivo en el rendimiento de la innovación de las empresas. Existe un efecto interactivo entre el potencial combinatorio del conocimiento y la diversidad del conocimiento, y su coordinación mutua mejora conjuntamente el rendimiento de la innovación empresarial. La complementariedad del aprendizaje ambidiestro modera significativa y positivamente la relación positiva entre el potencial de combinación de conocimientos y el rendimiento de la innovación empresarial.

Palabras clave: *red de conocimiento, complementariedad del aprendizaje ambidiestro, potencial de combinación del conocimiento, diversidad del conocimiento, fabricación automotriz.*

INTRODUCTION

A new round of industrial change is emerging, and how to enhance the innovation capability of firms to promote their development and maintain their core competitiveness has been a key concern of the academic community (Marín-Idárraga, Gonzalez, & Medina, 2016; Marín-Idárraga & Cuartas-Marin, 2019). Social network theory states that knowledge networks play an important role in promoting firm innovation (Yayavaram & Ahuja, 2008). A knowledge network is a knowledge-based cross-organizational relationship structure for dealing with the interactions of firms in absorbing and exchanging knowledge (Dong & Yang, 2016). Most researchers on knowledge networks have focused on the innovative advantages offered by network embedding (Wang, Rodan, Fruin, & Xu, 2014). However, there are fewer studies on firm knowledge networks from the perspective of feature attributes. It has been shown that the feature of knowledge networks indicates the range of combinatorial opportunities in a firm's technology domain and their potential for combining other knowledge elements that exist outside the firm's knowledge stock (Yayavaram & Chen, 2015), i.e., knowledge diversity and combination potential of knowledge. Knowledge diversity refers to the extent to which a firm's knowledge elements are dispersed across many technology subcategories or concentrated in a few technology areas (Guan, Zhang, & Yan, 2017). The combinatorial potential of an organization's knowledge is reflected in its portfolio history, i.e., the number of direct links of knowledge elements in the knowledge network (Wang et al., 2014). On the one hand, knowledge diversity can reduce the learning costs of firms, accelerate the rate of knowledge accumulation, and enhance innovation performance. On the other hand, the combination potential of knowledge provides firms with experience in technology combinations and breaks path dependencies. However, some scholars argue that knowledge networks may increase the risk of knowledge spillovers to the detriment of firm innovation (Li, Lin, & Xie, 2020). In addition, whether there are complementary or alternative roles between the combination potential of knowledge and knowledge diversity needs to be further explored. Therefore, clarifying the relationship between knowledge networks and firm innovation is of great practical importance to improve the innovation capability of firms.

In contrast to social network theory, which emphasizes the acquisition of heterogeneous resources through knowledge networks, ambidextrous learning theory suggests that the resources acquired by firms need to assimilate, integrate, and utilize the resources they obtain from external sources to help them improve their innovation performance (Jin, Wang, Chen, & Wang, 2015; Wang, Chen, & Fang, 2018). Ambidextrous learning is the ability to pursue both exploratory and exploitative learning (March, 1991). Throughout the existing literature, scholars have mainly explored the mechanisms of the role of ambidextrous learning on innovation (Cheng, Xu, Li, & Zhang, 2022; Wu, Chen, Shao, & Lu, 2021; Xie, Wu, & Devece, 2022). There is a lack of in-depth exploration of ambidextrous learning research (Cao, Gedajlovic, & Zhang, 2009). Venkatraman (1989) argues that there are complementary effects in ambidextrous learning, which reveals a firm's ability to acquire, integrate, and use knowledge resources. However, existing research has failed to include the complementarity of ambidextrous learning as a weighting factor in the research framework of a knowledge network and firm innovation, and there is a lack of understanding of the process mechanisms of how the complementarity of ambidextrous learning moderates the relationship between knowledge network and firm innovation. Therefore, further empirical research is needed.

This paper contributes to studying knowledge networks and ambidextrous learning in three ways. First, we theoretically develop and empirically test the specific impact of knowledge networks on innovation performance and further examine the interaction of the feature attributes of knowledge networks on innovation performance. Second, we propose a holistic model that integrates knowledge networks and the complementarity of ambidextrous learning and investigates their joint impact on innovation performance, which has not been explored in the existing literature. Third, this study considers the complementarity of ambidextrous learning as a weighting factor and explores the moderating pathways through which the complementarity of ambidextrous learning affects the relationship between knowledge networks and firm innovation, providing new insights into ambidextrous learning research.

First, we present a literature review, followed by the methodology and variable measurements. Finally, the results and conclusions, future research lines, and the study's limitations are set out.

THEORETICAL BACKGROUND AND HYPOTHESES

Combination potential of knowledge and firm innovation performance

The combination potential of knowledge is a key indicator of the feature attributes of a knowledge network, reflecting the fit degree of an enterprise's knowledge elements with those of others within the network (Wang et al., 2014). A high combinatorial potential of knowledge elements means that they are more visible in the knowledge network of the whole industry, indicating that the firm has more experience in successfully combining the knowledge elements with other knowledge elements, which is conducive to enhancing the firm's innovation level (Fleming, Mingo, & Chen, 2007). In addition, organizations with high portfolio potential have more opportunities to collaborate with other organizations (Yayavaram & Ahuja, 2008). In particular, cognitive distance from partner organizations ensures the novelty of knowledge and information sources, providing favorable conditions for firm innovation and promoting the integration of knowledge (Hu, Li, & Tang, 2019). However, due to the uncertainty of innovation, the cognitive distance may also prevent firms from collaborating, thus not taking better advantage of opportunities and reducing their innovation output (Granstrand, 1998). Moreover, there is a natural limit to the combinatorial potential of knowledge, i.e., the core knowledge elements may eventually exhaust their scientific, technological, and commercial value (Wang et al., 2014). When a knowledge element finally reaches this point, its further combination with other knowledge elements will no longer be valid (Carnabuci & Bruggeman, 2009; Sun & Gong, 2020). Therefore, a too-high combinatorial potential of knowledge will also harm innovation performance. Thus, the following hypothesis is proposed:

> H1: The combination potential of knowledge has an inverted U-shaped impact on firm innovation performance.

Knowledge diversity and firm innovation performance

Knowledge diversity refers to how the knowledge elements of a firm are dispersed across many technology sub-categories or concentrated in a few technology areas. It reflects the richness of the knowledge elements contained in a firm and is another critical indicator of the feature attributes of a knowledge network (Guan et al., 2017). Carnabuci and Operti (2013) argue that the more knowledgeable a firm is, the easier it is to explore potential technological areas and acquire new elements of knowledge and that the new knowledge acquired by the firm collides and combines with internal knowledge to increase the chances of generating new ideas and new approaches to the problems and challenges that arise in the innovation process. In addition, from the perspective of cognitive distance, having a similar knowledge base is a prerequisite for firms to collaborate effectively (Ning & Guo, 2022). It becomes easier to communicate, collaborate, and share knowledge between firms when they have a rich knowledge base (Ensign, Lin, Chreim, & Persaud, 2014; Marrocu, Paci, & Usai, 2013). The formation and maintenance of collaborative relationships are facilitated because of the similar knowledge base of each one (Mancusi, 2008). On the other hand, a diverse body of knowledge facilitates the effective absorption of different knowledge in an organization (Zahra, Ireland, & Hitt, 2000). An organization's ability to absorb knowledge is limited by its a priori knowledge (Cohen & Levinthal, 1990). An excessively homogeneous knowledge base will inevitably affect a firm's ability to absorb and utilize new knowledge, weakening its ability to adapt to the competitive environment and future markets. Therefore, the following hypothesis is set forth:

> H2: Knowledge diversity has a positive effect on firm innovation performance.

Interactive impact of knowledge network

There are complementary effects between combination potential of knowledge and knowledge diversity. This complementary effect is mainly reflected in a firm with a diverse knowledge base having a rich portfolio of knowledge opportunities. High knowledge diversity promotes active exchange among network members, facilitating the flow of knowledge within the network and significantly increasing opportunities for new knowledge combinations (Fleming, 2001).

Thus, higher knowledge diversity facilitates firms to enhance the suitability of knowledge elements to be combined with others, mapping the potential of the knowledge portfolio to be enhanced (Carnabuci & Bruggeman, 2009). In contrast, there is a natural limit to the combination potential of knowledge, i.e., knowledge diversity will simultaneously enhance the role of the knowledge combination potential as a facilitator and a hindrance to innovation in the firm. On the other hand, firms with a high combination potential of knowledge will attract other firms to cooperate with them. Then, in the process of cooperation, they acquire a diversity of technological knowledge, enriching their existing knowledge base and facilitating their innovation (Yayavaram & Ahuja, 2008). Thus, the following hypothesis is proposed:

> H3: The combination potential of knowledge and knowledge diversity have interactive effects on firm innovation performance.

Moderating role of complementarity of ambidextrous learning

March (1991) first proposed ambidextrous learning, including exploitative and exploratory learning. Exploitative learning is an applied extension of existing knowledge assets, while exploratory learning is a learning activity different from the existing knowledge base. Gupta, Smith and Shalley (2006) argue that the types of learning supporting exploration and exploitation are interrelated and can coincide rather than mutually exclusive. Based on Venkatraman's (1989) strategic matching theory, firms should combine exploratory learning and exploitative learning to achieve complementary effects because ambidextrous learning can effectively leverage the complementary knowledge and resources between exploratory and exploitative learning to improve a firm's innovation performance.

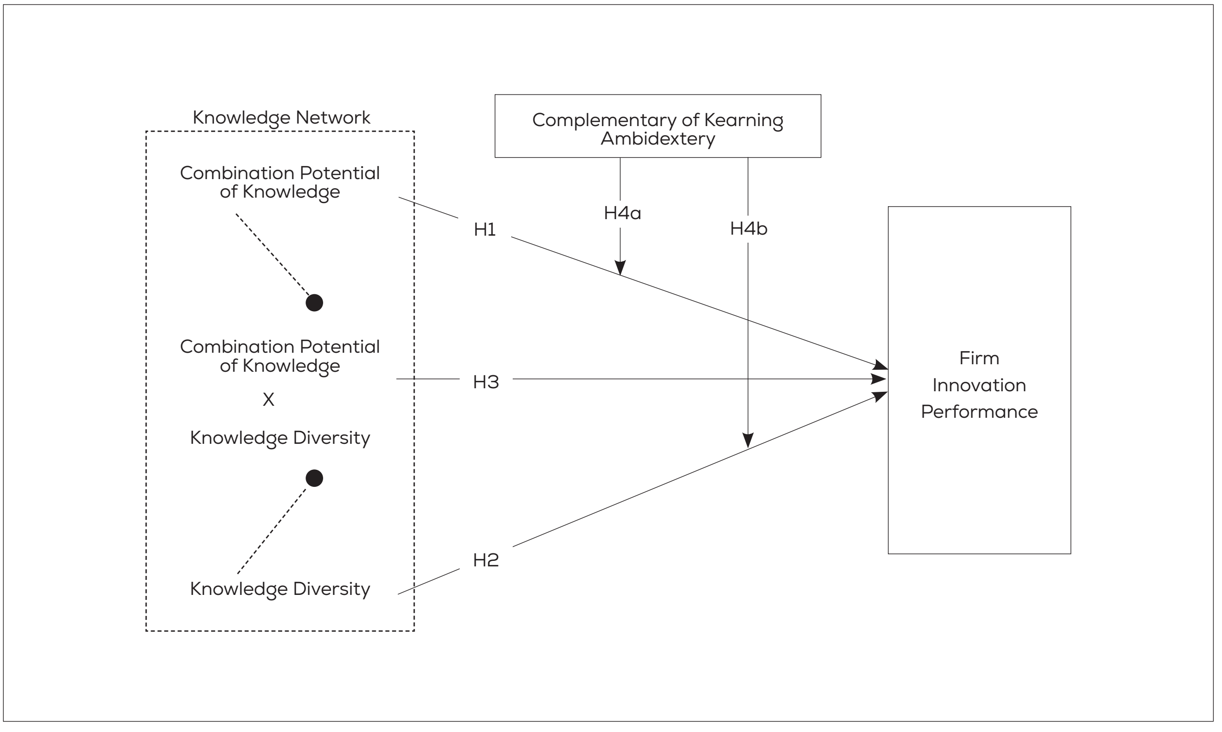
The complementarity of ambidextrous learning refers to the process by which exploratory and exploitative learning complement and reinforce each other. In contrast, organizations that pursue a matching of two learning abilities have more development space to improve their innovation capabilities (Wei, Yi, & Guo, 2014). On the one hand, the combination potential of knowledge that has not reached a critical point means that the firm has been unable to grasp the existing knowledge and fully capture its total value. Exploitative learning focuses on incremental innovation that meets current customer and market needs (Enkel, Heil, Hengstler, & Wirth, 2017). At this point, firms dynamically adjust their investments in developmental learning to deepen how they combine existing knowledge, improve the consistency of their knowledge, and facilitate technological practice development and firm performance. It can also quickly generate short-term performance (Phelps, 2010) and provide a robust financial guarantee for exploratory learning in the enterprise. Furthermore, exploratory learning improves the usage of existing technology and assists firms in acquiring new knowledge across borders. Thus, firms with high complementarity of ambidextrous learning have considerable integration capabilities, and firms can leverage new knowledge promptly to drive the reconfiguration of existing knowledge.

On the other hand, if the combination potential of knowledge has not yet reached critical levels, increasing the complementarity of ambidextrous learning will help firms improve their absorptive capacity, promote knowledge exploration in the process of new product development, and increase their combination potential of knowledge (Fang, Wang, & Chen, 2017). At the same time, the increasing absorptive capacity of firms will also improve the absorption and application of external heterogeneous knowledge, helping enterprises effectively use existing knowledge, create new knowledge and enhance the role of knowledge diversity on firms' innovation performance. It can be seen that the complementarity of ambidextrous learning not only helps firms acquire new knowledge and reduce the risk of instability and high costs during the development of new products but also helps firms have overall control of technological development trends and thus consolidate their sustainable competitive advantage. Therefore, we propose:

H4a: The firm's complementarity of ambidextrous learning positively moderates the positive relationship between the combination potential of knowledge and firm innovation performance.

H4b: The firm's complementarity of ambidextrous learning positively moderates the relationship between knowledge diversity and firm innovation performance (see Figure 1).

Figure 1. Research framework



Source: Elaborated by authors.

METHOD

Research setting, data, and samples

We choose the Chinese automobile manufacturing industry as our sample for empirical analysis for four reasons. First, automobile manufacturing is a vast socio-economic system project. Unlike ordinary products, automobile products are highly integrated end products and belong to a specific knowledge-intensive industry. Its need to build new knowledge has intensified in the context of increasing resource and knowledge search. Thus, studying automotive manufacturing knowledge portfolios and knowledge diversity is particularly important. Second, there is a strong incentive to develop and apply for intellectual property rights in the automotive manufacturing sector. Firms often use patents to protect their innovation efforts (Xu, Li, & Zhou, 2019), providing a wealth of patent data for empirical evidence. Third, China has been the world's largest producer of automobiles since 2009. Currently, automobile manufacturing is China's second largest industry after real estate. Fourth, a new round of technological innovation and new industries are developing rapidly. China's auto manufacturing industry is accelerating the profound transformation from "Made in China" to "Created in China." Firms in this industry also seek to adapt to the new technological revolution and achieve breakthrough innovation.

This paper takes 116 listed firms in the automobile manufacturing industry from 2010 to 2018 as research samples. The selection method of sample firms draws on Zhang and Luo's (2020) study, and the selected sample firms need to keep patent applications for two consecutive periods. At the same time, ST or *ST firms were excluded and individuals with missing data of primary variables were discarded. Finally, 146,823 patent data from 116 automotive manufacturing industries were obtained. In addition, this paper constructs a firm's knowledge network with a 3-year rolling timeline, indicates specific knowledge elements by the first four digits of the international patent classification number (IPC subclasses), and then calculates the value of each index (Xu & Zeng, 2021). The relevant data mainly comes from the China Stock Market & Accounting Research Database (CSMAR) and State Intellectual Property Office patent database.

VARIABLES

Dependent variable

The dependent variable in this study is firm innovation performance (IP). Innovation performance refers to the scientific and technological results obtained by the firm in its innovation activities (Kash & Rycoft, 2000). In the existing literature, patent data were considered a reliable indicator of a firm's innovation performance by considering its R&D activities (Sampson, 2007). Despite some apparent limitations, patent data have become the most widely used metric in the academic community to measure the firm's innovation performance (Zhang, Zhang, Zhu, & Liu, 2020). The performance of innovation activities has a certain lag. We adopted a one-year lag to reduce potential problems associated with endogeneity (Yao, Li, & Li, 2020). For example, the explanatory variables are calculated for the years 2010-2012, using data on the patents filed by the firm in 2013 to measure the firm's innovation performance.

Independent variables

Among the measures of knowledge diversity (KD), scholars commonly use the Herfindahl index or entropy method to measure it (Jiao, Xu, Li, & Yang, 2021; Jung, Kim, & Lee, 2021). One of the most widely used is the Herfindahl index method, and this paper also uses the Herfindahl index to calculate the firm's knowledge diversity. The following formulas were used:

$$KD = 1 - \sum_{i}^{n} p_i^2 \qquad (1)$$

Where KD stands for knowledge diversity, and n denotes the technology category involved based on the first four digits of International Patent Classification (IPC). P_i indicates the ratio of the number of patents of technology category i to the total number of patents of the firm. For example, if a firm has four patent data, the patent classification numbers are shown in Table 1. The firm's knowledge diversity can be calculated as KD= $[1-(2/4)^2- (2/4)^2- (2/4)^2- (1/4)^2]$ =0.1875. KD is between 0 and 1, and the closer the calculation is to 1, the higher the degree of knowledge diversity.

Table 1. Examples of firm knowledge diversity

Patent	Classification number
1	G01M、G01B、G01B
2	G01M、G01F
3	B23K、G01B
4	B23K

Source: Elaborated by authors.

The combination potential of knowledge (CPK) of a firm is measured by the average portfolio potential of all its knowledge elements (Brennecke & Rank, 2017). The combination potential of knowledge elements is reflected by their degree of centrality in the knowledge network (Wang, Yang, & Guo, 2021). If two knowledge elements appear together in a patent, they are connected in a knowledge network. The calculation formula is:

$$C_D(i) = \frac{\sum_{j=1}^{n} X_{ij}}{n} (i \neq j) \qquad (2)$$

Where X_{ij} denotes whether node j and i are directly connected, denoted by 0 and 1, and n denotes the number of nodes.

Moderating variable

According to Venkatraman's (1989) strategic matching theory, strategic matching can be expressed as a complementary relationship between variables and is measured by the multiplicative term of the variables. Based on this theory, the complementarity of ambidextrous learning can be measured by the interaction term of exploratory and exploitative learning to reflect the matching and interaction status. Also, this paper uses IPC subcategories as a proxy variable for knowledge elements and compares the organizational knowledge elements in year t with those from t-3 to t-1 (Katila & Ahuja, 2002). A patent with an IPC subclass is defined as exploitative learning if the firm has an IPC subclass in the latter stage that was present in the previous stage. Conversely, it is exploratory learning (Li, Li, & Zhou, 2022). The formula for the complementarity of ambidextrous learning is:

$$AMB_{IT} = Exploratory\ learning_{it} \times Exploitative\ learning_{it} \qquad (3)$$

Control variables

The control variables involved in this paper mainly include the firm's return on equity, scale, R&D intensity, and age. The firm's age (AGE) is measured using the difference between the firm's founding time and year t (Dai, Zeng, Qualls, & Li, 2018). Firm size (SIZE) is calculated by the logarithm of the firm's revenue (Ahuja & Katila, 2001). The return on net assets of the firm (ROE) is measured by calculating the ratio of net income to the average balance of shareholders' equity (Yao, Gao, & Sun, 2020). Firm R&D intensity (RD) is then measured by the ratio of R&D investment to operating revenue (Zhao, Shao, & Wu, 2019).

ANALYSIS AND RESULTS

Regression models

Table 2 shows the descriptive statistics of the variables using Stata 16.0. The degree of knowledge diversity in China's automotive industry is high, with a standard deviation of 0.16, indicating that knowledge diversity varies less among enterprises. The average combination potential of knowledge was 2.65 with a standard deviation of 2.47, indicating that the mean value of degree centrality of knowledge elements did not differ significantly among firms. The variance inflation factor of each variable is much less than the threshold value of 5, indicating no multicollinearity problem. The regression analysis results are presented in Table 3. In this study, the results of innovation performance data show the characteristic of discrete non-negative integers and over-dispersion; the variance is much larger than the mean. Also, we conducted the Hausman test and finally chose a negative binomial regression model with fixed effects.

Table 2. Correlation and descriptive statistics

	Mean	S.D.	1	2	3	4	5	6	7	8	VIF
IP	201.74	449.71	1								–
CPK	2.65	2.47	0.709***	1							1.60
KD	0.81	0.16	0.315***	0.201***	1						1.46
AMB	2.54	1.17	0.633***	0.543***	0.517***	1					2.24
ROE	0.08	0.12	0.043	0.003	-0.044	0.039	1				1.06
AGE	18.18	4.95	0.086***	0.112***	0.071*	0.115***	-0.028	1			1.10
SIZE	9.51	0.67	0.644***	0.497***	0.443***	0.661***	0.138***	0.290***	1		2.26
RD	4.32	1.93	0.025	0.140***	0.109***	0.102***	-0.184***	-0.053	-0.150***	1	1.18

Source: Elaborated by authors.

Six regression models were developed based on the study hypotheses, and variables involving interaction terms were standardized, as shown in Table 3. Model 1 is the foundation model, which primarily examines the impact of control factors on firm innovation performance. All control variables have a considerable positive impact on firm innovation performance. On the one hand, this indicates that the longer a firm has been established and the more knowledge it has accumulated, the higher the firm's innovation performance. On the other hand, larger firms have more resources and technology and greater R&D efforts, which can improve a firm's innovation performance.

Model 2 adds the primary and secondary terms of combination potential of knowledge to model 1 to test the relationship between combination potential of knowledge and firm innovation performance, and the regression results of model 2 show a significant inverted U-shaped relationship between the two (β=0.4254, $p<0.01$; β=-0.2824, $p<0.01$). Thus, hypothesis 1 is supported. Model 3 adds knowledge diversity to model 1 to test the linear relationship between knowledge diversity and innovation performance. From model 3, it can be seen that there is a significant positive relationship between knowledge diversity and innovation performance (β=0.1057, $p<0.01$), and hypothesis 2 is supported.

Model 4 was designed to test the effect of the interaction between the combination potential of knowledge and knowledge diversity on firms' innovation performance. The results showed that the interaction between the primary term of combination potential of knowledge and knowledge diversity was positive ($\beta=0.1220$, $p<0.1$), and the interaction between the quadratic term of combination potential of knowledge and knowledge diversity was negative ($\beta=-0.1946$, $p<0.01$). It suggests that knowledge diversity and the combination potential of knowledge reinforce each other, supporting hypothesis 3. Specifically, the combinatorial potential of knowledge reinforces the positive effect of knowledge diversity on innovation performance. On the other hand, knowledge diversity enhances the inverted U-shaped relationship between the combination potential of knowledge and innovation performance, i.e., it strengthens the effect of the combination potential of knowledge on innovation performance. It also accelerates the rate of diminishing the positive effect of the combination potential of knowledge. The results of Model 5 and Model 6 analysis indicate that the complementarity of ambidextrous learning significantly moderates the positive relationship between the combination potential of knowledge and innovation performance ($\beta=0.0686$, $p<0.01$), and hypothesis 4a is supported. In contrast, the moderating effect of complementarity of ambidextrous learning on knowledge diversity and the firm's innovation performance was not significant ($\beta=0.0032$, $p>0.1$), thus hypothesis 4b is not supported.

Table 3. Negative binomial model with fixed effects for innovation performance

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SIZE	0.2696*** (4.27)	0.2304*** (3.59)	0.2036*** (3.07)	0.1309* (1.87)	-0.2069*** (-3.88)	-0.2463*** (-4.19)
RD	0.1472*** (6.04)	0.1042*** (4.01)	0.1313*** (5.27)	0.0762*** (2.85)	0.0072 (0.47)	0.0116 (0.73)
AGE	0.3323*** (7.18)	0.2756*** (5.83)	0.3303*** (7.19)	0.2607*** (5.55)	0.2090*** (5.93)	0.3251*** (10.64)
ROE	0.0713*** (2.69)	0.0890*** (3.39)	0.0723*** (2.78)	0.0921*** (3.64)	0.0286*** (2.88)	0.0268** (2.56)
CPK		0.4254*** (5.63)		0.4190*** (5.55)	0.2500*** (3.60)	
CPK^2		-0.2824*** (-4.61)		-0.2000*** (-3.39)	-0.2460*** (-2.63)	
KD			0.1057*** (3.08)	0.1382*** (3.44)		0.0130 (0.44)
CPK*KD				0.1220* (1.78)		
CPK^2*KD				-0.1946*** (-3.20)		

Continue

Table 3. Negative binomial model with fixed effects for innovation performance Concludes

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
AMB					0.9249*** (34.79)	0.9159*** (32.55)
CPK*AMB					0.0686*** (2.97)	
KD*AMB						0.0032 (0.12)
Constant	1.2657*** (20.24)	1.3058*** (21.01)	1.2776*** (20.45)	1.3458*** (21.37)	2.5859*** (36.11)	2.5466*** (36.01)
Log Likelihood	-2798.4801	-2783.1798	-2793.1616	-2770.3887	-2192.2899	-2210.4528
Wald chi2	175.27***	240.18***	181.61 ***	273.29***	1956.70***	1602.00***

Note: Robust standard errors in parentheses. * p < 0. 1, ** p < 0. 05, *** p < 0. 01.
Source: Elaborated by authors.

Robust check

The robustness test results are provided in Table 4. This research employs a random effects model to validate the results' reliability. As can be seen from Table 4, hypothesis 4b in the robustness test still does not pass. The direction of all regression results is consistent and significant with the original regression, so the empirical results of this paper have good robustness.

Table 4. Robust check results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SIZE	0.4698*** (8.26)	0.4511*** (8.04)	0.4013*** (6.73)	0.3331*** (5.48)	0.1601*** (5.20)	0.0952** (1.97)
RD	0.1828*** (8.05)	0.1366*** (5.70)	0.1648*** (7.07)	0.1019*** (4.13)	0.0286** (2.30)	0.0463*** (3.20)
AGE	0.2151*** (5.02)	0.1313*** (3.03)	0.2132*** (5.04)	0.1112*** (2.65)	-0.0068 (-0.34)	0.1519*** (5.60)
ROE	0.0574** (2.27)	0.0748*** (3.04)	0.0582** (2.36)	0.0819*** (3.48)	0.0097 (1.12)	0.0086 (0.87)
CPK		0.5093*** (7.52)		0.5062*** (7.38)	0.4546*** (8.65)	
CPK^2		-0.3348*** (-6.12)		-0.2443*** (-4.51)	-0.4236*** (-5.82)	

Continue

Table 4. Robust check results

Concludes

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
KD			0.1288*** (3.65)	0.1941*** (4.81)		0.0208 (0.71)
CPK*KD				0.1686** (2.53)		
CPK^2*KD				-0.2261*** (-3.91)		
AMB					1.0009*** (41.81)	0.9795*** (35.08)
CPK*AMB					0.0641*** (3.46)	
KD*AMB						0.0178 (0.64)
Constant	1.2338*** (19.76)	1.2602*** (20.16)	1.2416*** (19.91)	1.2819*** (20.16)	2.4509*** (34.93)	2.4182*** (33.36)
Log Likelihood	-3647.8037	-3621.1659	-3640.1426	-3601.4826	-2897.9752	-2958.8797
Wald chi2	229.47***	353.45***	235.77***	401.93***	3463.07***	2036.95***

Note: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Elaborated by authors.

DISCUSSION

For Chinese listed firms in the automotive manufacturing industry, this study found an inverted U-shaped relationship between the combination potential of knowledge and firm innovation performance (H1). Existing studies have highlighted the positive impact of the combination potential of knowledge on firm innovation performance in various industries in China, including artificial intelligence (Zhang & Luo, 2020), radio communications (Li & Jian, 2022), and aerospace equipment manufacturing (Zhu, Ning, & You, 2022). As well as confirming the inverted U-shaped effect mentioned in H1, The research suggests that organizations with portfolio potential have access to heterogeneous information or knowledge conducive to innovation (Yayavaram & Ahuja, 2008) and enhance firms' innovation performance by helping them explore new technological opportunities (Rojas, Solis, & Zhu, 2018). Firms with high combination potential of knowledge can reduce external search costs (Shi, Zhang, & Zheng, 2019). However, as firms enhance how they combine knowledge elements, they will focus more on local search and develop core rigidity, diminishing marginal returns to technology, which is detrimental to their innovation performance (Xu, Li, & Zeng, 2017).

Second, knowledge diversity significantly positively affects a firm's innovation performance (H2). This result is consistent with the hypothetical expectations of this paper and with the existing literature on the relationship between knowledge diversity and innovation performance (Quintana-García & Benavides-Velasco, 2008; Zhang & Luo, 2020). The results suggest that the higher the knowledge diversity, i.e., the wider the knowledge domain spanned by knowledge units, the more organizations can generate new connections and ideas. It allows organizations to solve specific technological problems differently and promotes the firm's innovative performance (Carnabuci & Operti, 2013).

Third, there is an interaction effect between knowledge diversity and the combination potential of knowledge, and the mutual coordination between them promotes the improvement of firm innovation performance (H3). Although there are few relevant studies at the micro level, the findings of this paper are consistent with some authors (Carnabuci & Operti, 2013; Wang & Wang, 2018). Research shows that innovation comes from combining or reorganizing existing knowledge elements, and knowledge diversity enhances the possibility of combination or reorganization (Wanzenböck & Piribauer, 2018), which improves a firm's innovation performance. The combination potential of knowledge can improve firms' absorption and transformation of diverse technologies through, for example, technology spillovers, and the two dimensions of knowledge networks are mutually reinforcing.

Fourth, the complementarity of ambidextrous learning positively moderates the positive relationship between the combination potential of knowledge and firm innovation performance (H4a). In contrast, the moderating effect on the relationship between knowledge diversity and firm innovation performance is not significant (H4b). The existing studies on the effect of ambidextrous learning on innovation are more in-depth but ignore its moderating role (Colombo, Doganova, Piva, D'Adda, & Mustar, 2015). To this end, this paper further analyzes the moderating role of complementarity of ambidextrous learning on knowledge networks and innovation performance. The results show that the complementarity of ambidextrous learning promotes better development of the combination potential of knowledge and innovation. The complementary nature of ambidextrous learning helps firms to consolidate their existing knowledge base, explore new knowledge areas, and increase their combination potential of knowledge, thereby improving their innovation performance. The moderating effect of complementarity of ambidextrous learning between knowledge diversity and firm innovation performance is insignificant. The reason may be that when an enterprise has high knowledge diversity, it will have more opportunities to explore the combination or reorganization of its knowledge elements (Guan et al., 2017), thus weakening the dependence on expanding its knowledge base through exploratory learning. The core of the complementary dimension is the mutually beneficial effect of exploratory and exploitative learning. Therefore, the moderating effect is insignificant.

CONCLUSIONS AND IMPLICATIONS

This study theoretically developed and empirically examined the direct and interactive effects of the combination potential of knowledge and knowledge diversity on firm's innovation performance from a knowledge network perspective. It also further investigated the moderating role of the complementarity of ambidextrous learning in this process. The findings confirm an inverted U-shaped relationship between the combination potential of knowledge and innovation performance, with knowledge diversity positively affecting firms' innovation performance. Moreover, there is an interactive effect between the combination potential of knowledge and knowledge diversity, and the mutual coordination between the two contributes to improving innovation performance. Furthermore, the complementarity of ambidextrous learning moderated the positive relationship between the combination potential of knowledge and innovation performance. However, the complementarity of ambidextrous learning did not play a moderating role in the relationship between knowledge diversity and innovation performance.

Theoretical implications

This study offers three significant contributions. First, it enriches the existing innovation research and knowledge management theories. This study combines the network perspective of innovation and the knowledge perspective, constructs a research framework on the influence of knowledge networks on firms' innovation performance, and refines and provides empirical evidence on knowledge networks dimensions of innovation networks and firms' innovation performance. Moreover, this paper reveals an inverted U-shaped relationship between the combination potential of knowledge and firm innovation performance, providing new insights into firms' use of knowledge networks to improve innovation performance. At the same time, unlike most studies that focus on the relationship between knowledge networks' embedding features and firms' innovation performance, this paper expands the study of the factors influencing innovation performance from an interaction perspective. Therefore, this paper is an essential addition to the existing innovation and knowledge management theories.

Second, this paper studies the moderating role of the complementarity of ambidextrous learning as a knowledge network on firms' innovation performance. Prior research has focused more on the direct and mediating impact of ambidextrous learning on firm innovation performance (Colombo et al., 2015; Wei et al., 2014). This study provides new perspectives on controlling the complementarity of ambidextrous learning to enhance the combination potential for knowledge. It enriches the application of ambidextrous learning theory in different scenarios, expands the mechanism of the moderating effect of ambidextrous learning theory, and provides a theoretical reference for the automotive manufacturing industry to choose an appropriate approach.

Third, this paper uses panel data from Chinese automotive manufacturing industry for hypothesis testing, which not only incorporates time as an important contextual factor into the consideration of the theoretical model but also reflects the changing dynamics of the firm's knowledge network and shows the dynamic nature of the impact of knowledge networks on firm innovation, which helps to enrich the research findings on the relationship between knowledge network and firm innovation in the Chinese context.

Practical implications

This study also has managerial implications. First, the combination potential of knowledge and knowledge diversity are important channels to improve firm innovation performance. On the one hand, firms should weigh the costs and benefits of combining knowledge elements and allocate internal resources and efforts reasonably to achieve an optimal combination. On the other hand, firms can invest further resources in developing new knowledge elements and increase the firm's knowledge diversity level.

Second, there is an apparent interactive effect between the combination potential of knowledge and knowledge diversity, and firms should attach importance to the joint improvement of the combination potential of knowledge and knowledge diversity, for example, by strengthening communication among network members to realize the strategic synergy of "1+1>2" and promote the innovative development of firms.

Third, based on the positive moderating effect of the complementarity of ambidextrous learning, the automotive manufacturing industry should strengthen the development of ambidextrous learning ability. Firms must explore new knowledge elements through exploratory learning to ensure their future innovation capabilities and tap into existing knowledge elements through exploitative learning to ensure current competitive advantages, promoting knowledge networks' development and improving innovation performance.

Limitations and future research

This research had some significant limitations. First, the study of knowledge networks has yet to be further developed. This paper examines the specific impact of the combination potential of knowledge and knowledge diversity on firm innovation. However, the features of knowledge networks can also be developed from the perspective of network embedding, such as network cohesion, network density, and other indicators. The interaction between collaboration networks and knowledge networks can also be studied to allow for a more thorough examination of knowledge networks.

Second, this study only explores the moderating effect of the complementarity of ambidextrous learning, but the "knowledge network-firm innovation performance" relationship may be influenced by other external factors. For example, the moderating effects of dynamic capabilities and cross-border search help firms build knowledge networks and ultimately affect innovation performance. So, future research could focus in this direction.

Third, although we test our hypothesis using patent data of listed automotive companies, this may not be generalized to other fields. As such, future studies may incorporate different industries in the sampling process to validate the findings and identify the boundaries of the findings.

REFERENCES

Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, *22*(3), 197-220. http://dx.doi.org/10.1002/smj.157

Brennecke, J., & Rank, O. (2017). The firm's knowledge network and the transfer of advice among corporate inventors: A multilevel network study. *Research Policy*, *46*(4), 768-783. http://dx.doi.org/10.1016/j.respol.2017.02.002

Cao, Q., Gedajlovic, E., & Zhang, H. (2009). Unpacking organizational ambidexterity: Dimensions, contingencies, and synergistic effects. *Organization Science*, *20*(4), 781-796. http://dx.doi.org/10.1287/orsc.1090.0426

Carnabuci, G., & Bruggeman, J. (2009). Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. *Social Forces*, *88*(2), 607-641. http://dx.doi.org/10.1353/sof.0.0257

Carnabuci, G., & Operti, E. (2013). Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strategic Management Journal*, *34*(13), 1591-1613. http://dx.doi.org/10.1002/smj.2084

Cheng, H., Xu, X., Li, Z., & Zhang, Z. (2022). The synergy of inventor cooperative network dual embeddedness and firm innovation: The mediating role of ambidextrous learning. *Technology Analysis & Strategic Management*, 1-16. http://dx.doi.org/10.1080/09537325.2021.2021175

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 128-152. http://dx.doi.org/10.2307/2393553

Colombo, M. G., Doganova, L., Piva, E., D'Adda, D., & Mustar, P. (2015). Hybrid alliances and radical innovation: The performance implications of integrating exploration and exploitation. *The Journal of Technology Transfer*, *40*(4), 696-722. http://dx.doi.org/10.1007/s10961-014-9363-x

Dai, H., Zeng, D., Qualls, W. J., & Li, J. (2018). Do social ties matter for the emergence of dominant design? The moderating roles of technological turbulence and IRP enforcement. *Journal of Engineering and Technology Management*, *47*, 96-109. http://dx.doi.org/10.1016/j.jengtecman.2018.01.002

Dong, J. Q., & Yang, C. H. (2016). Being central is a double-edged sword: Knowledge network centrality and new product development in US pharmaceutical industry. *Technological Forecasting and Social Change*, *113*(1), 379-385. http://dx.doi.org/10.1016/j.techfore.2016.07.011

Enkel, E., Heil, S., Hengstler, M., & Wirth, H. (2017). Exploratory and exploitative innovation: To what extent do the dimensions of individual level absorptive capacity contribute? *Technovation*, *60*, 29-38. http://dx.doi.org/10.1016/j.technovation.2016.08.002

Ensign, P. C., Lin, C. D., Chreim, S., & Persaud, A. (2014). Proximity, knowledge transfer, and innovation in technology-based mergers and acquisitions. *International Journal of Technology Management*, 66(1), 1-31. http://dx.doi.org/10.1109/HICSS.2013.457

Fang, S. C., Wang, M. C., & Chen, P. C. (2017). The influence of knowledge networks on a firm's innovative performance. *Journal of Management & Organization*, 23(1), 22-45. http://dx.doi.org/10.1017/jmo.2016.32

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, *47*(1), 117-132. http://dx.doi.org/10.1287/mnsc.47.1.117.10671

Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3), 443-475. http://dx.doi.org/10.2189/asqu.52.3.443

Granstrand, O. (1998). Towards a theory of the technology-based firm. *Research Policy*, 27(5), 465-489. http://dx.doi.org/10.1016/S0048-7333(98)00067-5

Guan, J., Zhang, J., & Yan, Y. (2017). A dynamic perspective on diversities and network change: Partner entry, exit and persistence. *International Journal of Technology Management*, *74*(1-4), 221-242. http://dx.doi.org/10.1504/IJTM.2017.083613

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The interplay between exploration and exploitation. *Academy of Management Journal*, *49*(4), 693-706. http://dx.doi.org/10.5465/amj.2006.22083026

Hu, Q., Li, X., & Tang, W. (2019). Research on the influence mechanism of cognitive distance and social distance between supply chain enterprises on cooperative innovation performance. *Economic Survey*, 36(3), 110-117. http://dx.doi.org/10.15931/j.cnki.1006-1096.20190416.008

Jiao, J., Xu, Y., Li, J., & Yang, R. (2021). The evolution of a collaboration network and its impact on innovation performance under the background of government-funded support: An empirical study in the Chinese wind power sector. *Environmental Science and Pollution Research*, 28(1), 915-935. http://dx.doi.org/10.1007/s11356-020-10528-2

Jin, X., Wang, J., Chen, S., & Wang, T. (2015). A study of the relationship between the knowledge base and the innovation performance under the organizational slack regulating. *Management Decision*, 53(10), 2202-2225. http://dx.doi.org/10.1108/MD-05-2014-0253

Jung, S., Kim, K., & Lee, C. (2021). The nature of ICT in technology convergence: A knowledge-based network analysis. *Plos One*, *16*(7), e0254424. http://dx.doi.org/10.1371/journal.pone.0254424

Kash, D. E., & Rycoft, R. W. (2000). Patterns of innovating complex technologies: A framework for adaptive network strategies. *Research Policy*, 29(7-8), 819-831. http://dx.doi.org/10.1016/S0048-7333(00)00107-4

Katila, R., & Ahuja, G. (2002). Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, *45*(6), 1183-1194. http://dx.doi.org/10.5465/3069433

Li, N., Lin, R., & Xie, Z. (2020). Research on impact mechanism of exploratory innovation under multiple embedded in knowledge network and cooperation network. *Studies in Science of Science*, 38(1), 169-179. http://dx.doi.org/10.16192/j.cnki.1003-2053.2020.01.019

Li, P., & Jian, L. (2022). Network structure, knowledge base and enterprise innovation performance. *Complex Systems and Complexity Science*, *19*(02), 31-38. http://dx.doi.org/10.13306/j.1672-3813.2022.02.004

Li, X., Li, K., & Zhou, H. (2022). Impact of inventor's cooperation network on ambidextrous innovation in Chinese AI enterprises. *Sustainability*, *14*(16), 9996. http://dx.doi.org/10.3390/su14169996

Mancusi, M. L. (2008). International spillovers and absorptive capacity: A cross-country cross-sector analysis based on patents and citations. *Journal of International Economics*, *76*(2), 155-165. http://dx.doi.org/10.1016/j.jinteco.2008.06.007

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, *2*(1), 71-87. http://dx.doi.org/10.1287/orsc.2.1.71

Marín-Idárraga, D. A., & Cuartas-Marin, J. C. (2019). Relationship between innovation and performance: Impact of competitive intensity and organizational slack. *RAE-Revista de Administração de Empresas*, *59*, 95-107. http://dx.doi.org/10.1590/S0034-759020190203

Marín-Idárraga, D. A., Gonzalez, J. M. H., & Medina, C. C. (2016). The antecedents of Exploitation-Exploration and their relationship with innovation: A study of managers' cognitive maps. *Creativity and Innovation Management*, *25*(1), 18-37. http://dx.doi.org/10.1111/caim.12139

Marrocu, E., Paci, R., & Usai, S. (2013). Proximity, networking and knowledge production in Europe: What lessons for innovation policy? *Technological Forecasting and Social Change*, *80*(8), 1484-1498. http://dx.doi.org/10.1016/j.techfore.2013.03.004

Ning, L., & Guo, R. (2022). Technological diversification to green domains: Technological relatedness, invention impact and knowledge integration capabilities. *Research Policy*, *51*(1), 104406. http://dx.doi.org/10.1016/j.respol.2021.104406

Phelps, C. C. (2010). A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of Management Journal*, *53*(4), 890-913. http://dx.doi.org/10.5465/amj.2010.52814627

Quintana-García, C., & Benavides-Velasco, C. A. (2008). Innovative competence, exploration and exploitation: The influence of technological diversification. *Research Policy*, *37*(3), 492-507. http://dx.doi.org/10.1016/j.respol.2007.12.002

Rojas, M. G. A., Solis, E. R. R., & Zhu, J. J. (2018). Innovation and network multiplexity: R&D and the concurrent effects of two collaboration networks in an emerging economy. *Research Policy*, *47*(6), 1111-1124. http://dx.doi.org/10.1016/j.respol.2018.03.018

Sampson, R. C. (2007). R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal*, *50*(2), 364-386. http://dx.doi.org/10.5465/amj.2007.24634443

Shi, X., Zhang, Q., & Zheng, Z. (2019). The double-edged sword of external search in collaboration networks: Embeddedness in knowledge networks as moderators. *Journal of Knowledge Management*, 23(10), 2135-2160. http://dx.doi.org/10.1108/JKM-04-2018-0226

Sun, Y., & Gong, X. (2020). Superior position equal to greater influence? The moderating role of technological complexity. *Journal of Manufacturing Technology Management*, *31*(7), 1457-1480. http://dx.doi.org/10.1108/JMTM-07-2019-0269

Venkatraman, N. (1989). The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of Management Review*, *14*(3), 423-444. http://dx.doi.org/10.5465/amr.1989.4279078

Wang, C., Rodan, S., Fruin, M., & Xu, X. (2014). Knowledge networks, collaboration networks, and exploratory innovation. *Academy of Management Journal*, *57*(2), 484-514. http://dx.doi.org/10.5465/amj.2011.0917

Wang, J., Yang, N., & Guo, M. (2021). How social capital influences innovation outputs: An empirical study of the smartphone field. *Innovation*, *23*(4), 449-469. http://dx.doi.org/10.1080/14479338.2020.1810580

Wang, M. C., Chen, P. C., & Fang, S. C. (2018). A critical view of knowledge networks and innovation performance: The mediation role of firms' knowledge integration capability. *Journal of Business Research*, *88*, 222-233. http://dx.doi.org/10.1016/j.jbusres.2018.03.034

Wang, P., & Wang, Y. (2018). The characteristics of knowledge components and its effect on inventors' knowledge combination behavior: From the knowledge network perspective. *Business and Management Journal*, *40*(05), 92-107. http://dx.doi.org/10.19616/j.cnki.bmj.2018.05.006

Wanzenböck, I., & Piribauer, P. (2018). R&D networks and regional knowledge production in Europe: Evidence from a space-time model. *Papers in Regional Science*, *97*, S1-S24. http://dx.doi.org/10.1111/pirs.12236

Wei, Z., Yi, Y., & Guo, H. (2014). Organizational learning ambidexterity, strategic flexibility, and new product development. *Journal of Product Innovation Management*, *31*(4), 832-847. http://dx.doi.org/10.1111/jpim.12126

Wu, T., Chen, B., Shao, Y., & Lu, H. (2021). Enable digital transformation: Entrepreneurial leadership, ambidextrous learning and organisational performance. *Technology Analysis & Strategic Management*, 33(12), 1389-1403. http://dx.doi.org/10.1080/09537325.2021.1876220

Xie, X., Wu, Y., & Devece, C. (2022). Is collaborative innovation a double-edged sword for firms? The contingent role of ambidextrous learning and TMT shared vision. *Technological Forecasting and Social Change*, *175*, 121340. http://dx.doi.org/10.1016/j.techfore.2021.121340

Xu, L., Li, J., & Zeng, D. (2017). How does knowledge network affect a firm's explorative innovation? The contingent role of R&D collaborations. *Technology Analysis & Strategic Management*, 29(9), 973-987. http://dx.doi.org/10.1080/09537325.2016.1260105

Xu, L., Li, J., & Zhou, X. (2019). Exploring new knowledge through research collaboration: The moderation of the global and local cohesion of knowledge networks. *The Journal of Technology Transfer*, *44*(3), 822-849. http://dx.doi.org/10.1007/s10961-017-9614-8

Xu, L., & Zeng, D. (2021). When does the diverse partnership of R&D alliances promote new product development? The contingent effect of the knowledge base. *Technology in Society*, 65, 101590. https://doi.org/10.1016/j.techsoc.2021.101590

Yao, L., Li, J., & Li, J. (2020). Urban innovation and intercity patent collaboration: A network analysis of China's national innovation system. *Technological Forecasting and Social Change*, *160*, 120185. http://dx.doi.org/10.1016/j.techfore.2020.120185

Yao, Y., Gao, H., & Sun, F. (2020). The impact of dual network structure on firm performance: The moderating effect of innovation strategy. *Technology Analysis & Strategic Management*, 32(9), 1020-1034. http://dx.doi.org/10.1080/09537325.2020.1739263

Yayavaram, S., & Ahuja, G. (2008). Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. *Administrative Science Quarterly*, 53(2), 333-362. http://dx.doi.org/10.2189/asqu.53.2.333

Yayavaram, S., & Chen, W. R. (2015). Changes in firm knowledge couplings and firm innovation performance: The moderating role of technological complexity. *Strategic Management Journal*, *36*(3), 377-396. http://dx.doi.org/10.1002/smj.2218

Zahra, S. A., Ireland, R. D., & Hitt, M. A. (2000). International expansion by new venture firms: International diversity, mode of market entry, technological learning, and performance. *Academy of Management Journal*, *43*(5), 925-950. http://dx.doi.org/10.5465/1556420

Zhao, X., Shao, F., & Wu, C. (2019). Do stakeholder relationships matter? An empirical study of exploration, exploitation and firm performance. *Management Decision*, 59(4), 764-786. http://dx.doi.org/10.1108/MD-01-2019-0058

Zhang, S., Zhang, N., Zhu, S., & Liu, F. (2020). A foot in two camps or your undivided attention? The impact of intra-and inter-community collaboration on firm innovation performance. *Technology Analysis & Strategic Management*, 32(7), 753-768. http://dx.doi.org/10.1080/09537325.2019.1709636

Zhang, Z., & Luo, T. (2020). Knowledge structure, network structure, exploitative and exploratory innovations. *Technology Analysis & Strategic Management*, 32(6), 666-682. http://dx.doi.org/10.1080/09537325.2019.1693534

Zhu, J., Ning, H., & You, J. (2022). The influence of the structural features of patent cooperation network on enterprise exploratory innovation: A case study of the aviation equipment manufacturing enterprises. *Science and Technology Management Research*, 42(9), 128-135. http://dx.doi.org/10.3969/j.issn.1000-7695.2022.9.017

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CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

AUTHORS' CONTRIBUTION

Xiaoli Li: Conceptualization; Methodology; Writing – original draft; Writing – proofreading and editing.

Kun Li: Conceptualization; Data Curation; Methodology; Validation; ; Writing – original draft; Writing – proofreading and editing.