THE INFLUENCE OF FIRM KNOWLEDGE CHARACTERISTICS ON TECHNOLOGICAL INNOVATION: A MULTILEVEL NETWORK STRUCTURE PERSPECTIVE

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This study describes collaboration between firms and different organizations as a process of knowledge sharing, integrating inter-organizational collaboration networks and knowledge networks into a unified framework. It analyzes the bilayer structure of collaborative innovation networks, namely, the firm-knowledge bipartite network. The study investigates the impact of firm knowledge characteristics (diversity and uniqueness) on breakthrough and incremental innovation within collaborative innovation networks. The research employs patent data from Chinese A-share high-tech manufacturing companies listed from 2000 to 2018 and verifies the related hypotheses using a negative binomial regression model. The results suggest that, within collaborative innovation networks, firm knowledge diversity has a negative impact on breakthrough innovation but a positive impact on incremental innovation. On the other hand, firm knowledge uniqueness plays a positive role in breakthrough innovation but a negative role in incremental innovation. This study extends the understanding of firm technological innovation by considering both breakthrough and incremental innovation as distinct behaviors, providing a new perspective on the mechanisms underlying different innovation behaviors. By adopting a multilevel network structure approach to collaborative innovation, it contributes to a deeper understanding of internal
and external factors influencing firm innovation behavior and expands the application scope of social network analysis.

**Keywords:** knowledge characteristics; collaborative innovation network; multilevel network; breakthrough innovation; incremental innovation

**Introduction**

From the perspective of knowledge-based theory, collaborative innovation networks, the characteristics of organizational knowledge, and technological innovation exhibit a sense of "knowledge homogeneity." The essence of collaborative innovation networks lies in the interaction among multiple entities, wherein nodal entities can acquire resources from the external environment.

Enterprises actively engage in knowledge creation, storage, and utilization, utilizing their inherent knowledge-based characteristics by embedding them within the knowledge network (Wang et al., 2014).

Previous studies have shown that the innovation activities of enterprises are embedded not only in collaborative networks formed by research and development cooperation but also in knowledge networks formed by knowledge combinations. Enterprises enhance their innovation capabilities by acquiring, sharing, and utilizing knowledge within and across organizations (Cho & Linderman, 2020; Lu & Yu, 2020).

Fundamentally, enterprise innovation involves the aggregation, absorption, internalization, combination, externalization, and socialization of various internal and external knowledge elements, leading to the process of knowledge creation (Caloghirou et al., 2021).

Knowledge resources play a crucial role in the survival and development of enterprises (Hargadon & RI, 1997). The existing knowledge elements of an enterprise have an impact on its future direction and efficiency of innovation and serve as an important foundation for enterprise innovation.

Knowledge diversity reflects the extent of dispersed creative resource activities within a knowledge domain and determines the coverage of shared domain knowledge in enterprises, thereby influencing the bandwidth of communication channels (Caner et al., 2017). Knowledge uniqueness can reflect the generality of knowledge resource activities and is related to the difficulty of technology sharing and the coordination cost of knowledge resources.

This, in turn, affects the extent to which enterprises are willing to acquire external knowledge (Brennecke & Rank, 2017). Enterprises employ various learning processes based on their own knowledge characteristics to obtain necessary innovative knowledge. The acquisition of new technology and knowledge is also a primary motivation for enterprises to participate in collaborative networks (Ahuja, 2000).

In collaborative innovation networks, the process of enterprise innovation involves multiple organizational entities, various innovation elements, and diverse network positions, resulting in a range of innovation outcomes. This complex process raises questions about how the existing knowledge base of an enterprise influences different innovation behaviors and what characteristics these elements possess.
While scholars have explored the role of network relationships in enterprise innovation from a network structure perspective, recent research has emphasized the study of multilevel networks.

Gupta et al. (2007) argue that existing research on the relationship between networks and innovation primarily focuses on individual factors, which may lead to inconsistent conclusions. Considering that organizations are multilevel systems, the innovation activities of an organization should be viewed as a phenomenon consisting of at least two levels. It encompasses not only the actors themselves, such as individual innovators, teams, or enterprises, but also the environment in which they are embedded.

Therefore, analyzing enterprise innovation mechanisms from a multilevel or cross-level perspective is necessary to uncover the essence of enterprise innovation (Guan et al., 2015). The core question addressed in this paper is the impact of enterprise knowledge characteristics on different innovation behaviors within the collaborative innovation network, which constitutes a bipartite network structure consisting of firm-knowledge elements.

**Literature review**

**Theories used in the study**

This paper conceptualizes inter-firm collaborative innovation cooperation as a process of knowledge sharing by integrating the perspectives of knowledge-based view, social network theory, and knowledge search theory, while integrating inter-organizational collaboration networks and knowledge networks into a unified framework. The fundamental logic of social network theory suggests that team collaboration, facilitated by embedded interpersonal relationships, can provide advantages to members even in uncertain environmental conditions (Granovetter, 1985).

According to social network theory, conducting social network analysis is essential for understanding the interactive behaviors and performance outcomes of innovation activities in organizations. Only when an enterprise is embedded in close-knit network relationships can it gain access to more information and resources, thereby expanding its scale, enhancing its influence, and creating more value. Within a multi-level network structure, various types of connections and resource exchanges take place, allowing enterprises to acquire a broader range of resources and knowledge by being embedded in multi-level networks.

This helps them establish various potential connections and engage in multiple interactions. After understanding the resource characteristics of their collaborators, enterprises can choose different innovation strategies, leveraging the advantages of specific network levels and achieving better innovation performance. This multi-level network structure plays a significant role in facilitating innovation in enterprises.

The knowledge-based view has emerged as a prominent theory in recent years, positing that knowledge is the most crucial resource for firms and a key factor in their success. In contrast to the traditional resource-based view, the knowledge-based view considers knowledge as an intangible and transferable resource. It suggests that firms should maximize their value by acquiring, integrating, creating, and utilizing knowledge.

The theory of knowledge search holds that organizations can enhance their innovation capabilities by searching for external knowledge, creatively integrating it, and utilizing it to address innovation-related issues (Laursen & Salter, 2006).
Innovation is a process of recombining knowledge to find solutions, and exploring potential knowledge domains within the "search space" helps firms identify valuable technologies. The ultimate outcome of innovation activities depends on the interdependence between the knowledge being searched and the firm's own knowledge domain.

**Technological innovation**

Building on Schumpeter's notion of "creative destruction," Abernathy & Utterback (1978) introduced the concept of disruptive innovation and developed a theoretical framework in their seminal work on "Technological Paradigms and Technological Trajectories." They merged disruptive and incremental innovation within a unified theoretical framework, which represented a valuable complement and advancement to traditional organizational innovation theories, marking a significant theoretical development (Dosi, 1982).

The understanding of incremental innovation's essence has achieved relatively unified consensus within the academic community, with conceptual boundaries being quite similar. Most scholars commonly perceive incremental innovation as the utilization of existing technological potential to bring about relatively minor changes to current products. It entails the continuous improvement of existing products, services, and technologies, strengthening an organization's existing mature advantages and organizational capabilities. It demands relatively lower technological capabilities and scale requirements from the organization while maintaining the existing market rules.

It represents an extension of the existing technological paradigm, further reinforcing an enterprise's current competitive advantage (Garcia & Calantone, 2002; Ettlie, 1983; Lin et al., 2013).

On the other hand, disruptive innovation involves fundamental changes within technological transformations. In comparison to incremental innovation, disruptive innovation places greater emphasis on the path of technological innovation. Continuous technological innovation is essential for enterprise development, as it enables organizations to respond to rapidly changing markets and obtain sustainable competitive advantages. Disruptive technological innovations have the power to disrupt the existing value chain structure, form new value networks, and consequently trigger the reconstruction of overall technological competition nodes, market patterns, and industrial structures. They represent the core means for enterprises, industries, cities, regions, and even countries to gain opportunities and competitive advantages (Garcia & Calantone, 2002; Ettlie, 1983; Lin et al., 2013).

**Firm knowledge characteristics**

Knowledge is the foundation upon which businesses rely for survival. Essentially, enterprises are composed of knowledge elements, and the aggregation of various knowledge elements within an organization forms its knowledge base (Grant, 1996; Colombelli et al., 2013). Previous research has predominantly focused on the structural characteristics of knowledge elements, investigating the diversity, uniqueness, and complexity of knowledge within firms or individuals, as well as their impact on innovation activities and outcomes (Yayavaram et al., 2018; Mastrogiorgio & Gilsing, 2016; Trapido, 2015; Yayavaram & Chen, 2015).
Knowledge diversity reflects the dispersion of creative activities within a knowledge domain and determines the scope of shared knowledge, thereby influencing the bandwidth of communication channels within firms (Caner et al., 2017).

Knowledge uniqueness reflects the generality of knowledge activities and relates to the difficulty of sharing technology and the cost of coordinating knowledge, thus influencing firms' willingness to acquire external knowledge (Brennecke & Rank, 2017).

Inter-firm collaborative innovation networks, as knowledge-based bipartite and multi-level collaborative networks, exhibit fundamental distinctions from traditional cooperative networks or alliances in terms of value co-creation. Utilizing the dual-mode structure of collaborative innovation networks, the characteristics of knowledge diversity and uniqueness can be accurately identified, representing typical features of enterprises' knowledge elements.

Thus, it is necessary to analyze how the knowledge characteristics of diversity and uniqueness function within knowledge collaborative behaviors. This analysis aims to verify the mechanisms through which knowledge characteristics impact technological innovation from a knowledge element perspective. Therefore, for enterprises' technological innovation, it is important to understand how knowledge element attributes are employed and the effects of combining knowledge in specific ways. This perspective aligns with the key elements of individual behavior analysis in social network analysis through network structure characteristics (Scott, 1988).

**Research hypotheses**

Enterprise knowledge diversity and enterprise innovation in a collaborative innovation network

In the collaborative innovation bipartite network, the greater the diversity of knowledge within a firm, the greater its network accessibility. High accessibility implies that the firm can quickly access multiple knowledge elements distributed throughout the entire network at the shortest distance possible. This allows the firm to obtain various information more abundantly, rapidly, and conveniently, thereby enhancing its understanding and awareness of industry knowledge. Knowledge within an organization exhibits diverse characteristics.

From the perspective of knowledge relationships, the diversity of relationships among knowledge elements refers to the variety of combinations in the formation of new knowledge (Colombelli et al., 2013). Analyzing at the firm level, as the diversity of relationships among knowledge elements increases, the choices for knowledge combinations faced by the firm also become more numerous and complex.

With the sudden increase in information redundancy, the costs associated with knowledge management and maintenance within the firm also rise.

Additionally, if the relationships among knowledge elements become overly complex, it introduces uncertainty in the process of forming new knowledge (D’Este, 2005), further impacting the firm's innovative behavior. Based on the concept of disruptive innovation, this study proposes the following hypothesis:

**H1:** The diversity of knowledge within a firm hampers its disruptive innovation.

On the other hand, highly accessible firms can gain access to dispersed knowledge elements across networks, broadening the channels of knowledge flow and reducing knowledge distortion in the innovation process. The existing knowledge base of an enterprise is crucial for achieving incremental innovation.
The higher the diversity of knowledge and the larger the knowledge repository of an enterprise, the easier it is for them to form cooperative relationships with collaborators, thus promoting knowledge integration and innovation (Fleming, 2001).

The diversity of knowledge elements within an enterprise enables it to have more opportunities for combinations with knowledge elements from various technological domains, thereby possessing a greater number of technological pathways for specific problems (Ahuja & Morris, 2001).

This enhances the improvement of the core competencies of the enterprise (Liu et al., 2014). In other words, the richer the diversity of knowledge within an enterprise, the more advantageous it is to update and innovate existing technological knowledge. Based on the concept of incremental innovation, this paper proposes the following hypothesis:

H2: The diversity of knowledge within an enterprise has a positive effect on incremental innovation.

Knowledge distinctiveness refers to the unique knowledge possessed by a firm within a specific domain, which is heterogeneous and scarce compared to other firms, especially its collaborative partners (Schulz, 2001). The distinctive knowledge elements held by a firm are difficult to complement or combine with knowledge from other domains, thereby motivating researchers to focus more on the development of novel knowledge elements within specific domains, thereby fostering exploratory innovation (Carnabuci & Operti, 2013).

Higher knowledge distinctiveness helps firms mitigate the negative impact of heterogeneous knowledge and facilitates internal and external knowledge integration. Accumulating knowledge within a specialized domain also enhances the utilization of various external knowledge sources.

By establishing appropriate symbols and language, firms can accurately identify high-value knowledge relevant to their respective domains, thus expediting breakthrough innovation (Dogbe et al., 2020) and fostering the pursuit of breakthrough innovation activities. Therefore, this study proposes the following hypothesis:

H3: Knowledge distinctiveness positively influences breakthrough innovation in firms.

On the other hand, knowledge uniqueness represents an indicator of the extent to which a firm possesses knowledge that others are unfamiliar with. The uniqueness of knowledge is often the most critical core competency of a firm, implying that it possesses knowledge resources that are specific to the firm and cannot be reasonably imitated or substituted by other firms, characterized by scarcity and other essential features (Barney, 1991).

When a firm possesses unique knowledge, internal team members may be more focused on maintaining and protecting their proprietary knowledge and may be reluctant to share it with external parties. This "information hoarding" behavior can hinder the flow of knowledge within the organization, impacting inter-team interaction and collaboration, resulting in insufficient and inefficient knowledge sharing and impeding external interaction and knowledge renewal (Leonard & Sensiper, 1998; Hansen et al., 2013).

Firms with unique knowledge exhibit a self-realizing nature, wherein they emphasize safeguarding and leveraging their existing knowledge while being resistant to engaging with new or unfamiliar knowledge (Kogut & Zander, 1992).

Therefore, this study proposes the following hypothesis:

H4: Knowledge uniqueness inhibits firms’ incremental innovation.
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By synthesizing the logical derivation of the hypotheses mentioned above, the theoretical model of this paper is illustrated in Fig. 1.

![Conceptual framework](image)

**Figure 1 - Conceptual framework**
(compiled by co-authors)

**Materials and methods**

**Sample and data**

To test the hypotheses, this study constructs a collaborative innovation network using patent data and measures variables related to firm innovation. With the available sample data, A-share-listed companies are selected as the research subjects.

The patent information and basic data are obtained from the China Stock Market and Accounting Research (CSMAR) database and the annual reports of the listed companies. Regional characteristic data of the companies is obtained from the National Bureau of Statistics and the GDP reports of various provinces in China (2017 edition).

The sample companies predominantly belong to 17 industries, including computer, communication, and other electronic equipment manufacturing, chemical raw materials and chemical products manufacturing, pharmaceutical manufacturing, and other modern high-tech industries.

Applying the restriction of application dates from "20000101 to 20181231" as the yearly limitation, ST and *ST sample companies are excluded, and the dataset is filtered to include only high-tech manufacturing-related industries.

Finally, a sample of 515 companies with complete information disclosure was obtained for this study.

The specific industry composition of the sample companies is shown in Tab. 1.
Table 1 - Industry distribution of sample enterprises
(compiled by co-authors)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Number of Samples</th>
<th>Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer, communications, and other electronic equipment manufacturing</td>
<td>79</td>
<td>15.34%</td>
</tr>
<tr>
<td>C26: Manufacturing of chemical raw materials and chemical products</td>
<td>72</td>
<td>13.98%</td>
</tr>
<tr>
<td>C35: Special Equipment Manufacturing Industry</td>
<td>52</td>
<td>10.10%</td>
</tr>
<tr>
<td>C27: Pharmaceutical Industry</td>
<td>40</td>
<td>7.77%</td>
</tr>
<tr>
<td>C38: Manufacture of electrical machinery and equipment</td>
<td>39</td>
<td>7.57%</td>
</tr>
<tr>
<td>C34: General Machinery Manufacturing</td>
<td>28</td>
<td>5.44%</td>
</tr>
<tr>
<td>Software and information technology services</td>
<td>22</td>
<td>4.27%</td>
</tr>
<tr>
<td>Nonferrous metal smelting and rolling industry</td>
<td>22</td>
<td>4.27%</td>
</tr>
<tr>
<td>C37: Railway, Marine, Aerospace, and other transportation equipment manufacturing</td>
<td>15</td>
<td>2.91%</td>
</tr>
<tr>
<td>C30: Manufacture of non-metallic mineral products</td>
<td>14</td>
<td>2.72%</td>
</tr>
<tr>
<td>C36: Motor industry</td>
<td>13</td>
<td>2.52%</td>
</tr>
<tr>
<td>C29: Rubber and Plastic Products Industry</td>
<td>13</td>
<td>2.52%</td>
</tr>
<tr>
<td>Petroleum processing, coking, and nuclear fuel processing industries</td>
<td>8</td>
<td>1.55%</td>
</tr>
<tr>
<td>C33: Metal Products Industry</td>
<td>7</td>
<td>1.36%</td>
</tr>
<tr>
<td>C40: Instrumentation Manufacturing Industry</td>
<td>3</td>
<td>0.58%</td>
</tr>
<tr>
<td>C41: Other manufacturing</td>
<td>35</td>
<td>6.80%</td>
</tr>
<tr>
<td>Others (textile industry, fishery, animal husbandry, and other modern high-tech enterprises)</td>
<td>39</td>
<td>7.57%</td>
</tr>
</tbody>
</table>

Based on the sample data mentioned above, this study aims to construct 14 collaborative innovation bipartite networks based on the invention patent data that companies have applied for and obtained authorization for. The data cleaning procedure for the patent data is as follows:

Firstly, following the approach of Yayavaram & Ahuja (2008), this study extracts the first four digits of each patent's IPC classification code to represent different knowledge domains. Since the value of patents is time-sensitive and often loses a significant portion of their economic value within five years, considering the value decay of patents, this study adopts a five-year retrospective approach, as suggested by Gilsing et al. (2008), using patent data from the $t-5$ to $t-1$ periods to construct the firm-knowledge bipartite network in the $t$ period, which helps identify the diversity and uniqueness of knowledge within firms.

Furthermore, the observation period for independent variables, moderating variables, and control variables is set as 2001–2012, while the observation period for the dependent variable is set as 2006–2017.

Networkx and Numpy libraries in the Python language were utilized for constructing, filtering, processing, and computing the collaborative innovation networks. Ultimately, a dataset consisting of 515 focal companies and 1919 unbalanced panel observations from 2006–2017 was generated and used as the observed sample.
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Variable descriptions and measurements

Dependent variable
Breakthrough innovation (Exp1) and incremental innovation (Exp2) are measured following Ahuja and Lampert's (2001) method, which calculates the extent of a company's breakthrough in new technologies based on the number of second-level patent classifications it enters. This study adopts the classification method of the International Patent Classification (IPC) system in China, using the first four digits of the classification codes to represent the technological categories of companies.

The number of patents filed in each technological category during a specific period is then tallied. A patent is defined as breakthrough innovations if there have been no corresponding or similar patent applications in the past five years. Conversely, it is considered an incremental innovation if such applications exist.

Explanatory variables
Knowledge diversity (Kdiv) is measured using the approach proposed by Awate & Mudambi (2018), which utilizes node reachability in a bipartite network to assess knowledge diversity. Specifically, the inverse sum of the shortest path lengths between the focal firm and all knowledge element nodes in the network is calculated to determine the diversity of the firm's knowledge.

Knowledge uniqueness (Kuni) is measured following the methodology outlined by Brennecke & Rank (2017). Initially, the number of enterprises associated with each knowledge element in the network is computed. Then, this count is inverted, representing the reciprocal of the sum of the number of enterprises directly connected to the knowledge element in the bipartite network. This metric is used to gauge the uniqueness of knowledge.

Finally, the average of knowledge uniqueness indicators corresponding to knowledge elements owned by the same enterprise is calculated, as shown in Formula below.

$$KU = \frac{1}{m} \sum_{j=1}^{m} \frac{1}{n_j}$$

when $n_j$ represents the number of enterprises directly connected to knowledge element $j$ in the bipartite network, and $m$ denotes the number of knowledge domains in the company.

Control variables
As this study focuses on enterprises, it primarily controls for variables at the firm level. Firm patent accumulation (Pacculn) represents the level of knowledge accumulation in a specific technological field, providing abundant opportunities for knowledge search and enhancing the possibility of recombination innovation (Grillitsch & Nilsson, 2017).

In this study, the total number of patents applied for and granted by the firm in the five years prior to the sample period is used as a measure. Firm age (age) reflects the maturity of an enterprise's development and indicates the presence of a sound resource allocation system and collaborative management capability. Previous literature has confirmed that firm age is a key factor influencing innovation networks and performance.
Typically, it is measured by the years since the establishment of the enterprise or its initial public offering up to the current year. The firm size (ScalsIn) is an indicator of the resources available to a larger enterprise, which facilitates its innovation activities.

Regional GDP (GDPLn) is higher in regions with a higher economic level, which generally leads to more active research and development activities by enterprises (Li et al., 2014).

In this study, the natural logarithm of the GDP of the region in which the firm operates is included as a control variable in the regression analysis.

Firm ownership type (characteristic) includes categories such as state-owned enterprises, foreign-owned enterprises, privately-owned enterprises, and other types of enterprises. Year dummy variables (year) are introduced in the regression analysis to control for differences between different years. This study utilizes longitudinal panel data spanning 11 years (2006–2017).

Results

Descriptive statistics

Tab. 2 reports the descriptive statistics and correlation analysis of the variables. In the statistical sample, the average value of breakthrough innovation in the sampled companies is 3.09, while progressive innovation is 6.05. This indicates a greater preference for progressive innovation among the companies, suggesting that they have already accumulated a certain knowledge base. It further confirms that the sampled companies belong to the category of technological innovation firms, which aligns with the research question of this study.

Regarding the explanatory variables, the mean value of knowledge diversity in the bipartite network is 178.2, and the mean value of knowledge distinctiveness is 62.58. Overall, there is a high correlation between variables.

Furthermore, a further examination of all variables shows that the Variance Inflation Factor (VIF) values are all less than 10, indicating that the issue of multicollinearity has not significantly affected the regression results of this study.

Regression results

Due to the empirical data in this study covering the period from 2000 to 2018 of patent data from A-share listed companies, the variables consist of discrete non-negative count data, which violates the assumption of residual normality in linear models.

Therefore, both the Poisson and negative binomial models are ideal for estimating this type of data. The variance (mean = 3.09, variance = 21.55) is much greater than the mean, posing a challenge of overdispersion.

To address this issue (in contrast to the Poisson model, which assumes equal variance and mean of the dependent variable), the negative binomial regression model (Long, 1997) is employed in this study.

By comparing the Hausman test and the F-values after regression, a fixed-effects negative binomial regression is deemed more suitable for analyzing the theoretical model based on the sample data. The STATA/SE15.1
### Table 2 - Descriptive statistics and correlation analysis
(Compiled by co-authors)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exp1</td>
<td>3.090</td>
<td>4.640</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp2</td>
<td>6.050</td>
<td>12.72</td>
<td>1</td>
<td>0.693***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kdiv</td>
<td>178.2</td>
<td>32.02</td>
<td>0.316***</td>
<td>0.583***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kuni</td>
<td>62.58</td>
<td>94.34</td>
<td>-0.179***</td>
<td>-0.235***</td>
<td>-0.375***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paculin</td>
<td>4.370</td>
<td>1.570</td>
<td>0.427***</td>
<td>0.571***</td>
<td>0.630***</td>
<td>-0.390***</td>
<td>1</td>
<td></td>
<td></td>
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<tr>
<td>Age</td>
<td>14.72</td>
<td>5.210</td>
<td>-0.0190</td>
<td>0.0240</td>
<td>0.291***</td>
<td>-0.068***</td>
<td>0.137***</td>
<td>1</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Scalsln</td>
<td>22.19</td>
<td>1.680</td>
<td>0.560***</td>
<td>0.291***</td>
<td>0.539***</td>
<td>0.113***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>GDPln</td>
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<td>0.670</td>
<td>-0.099***</td>
<td>-0.080***</td>
<td>0.00500</td>
<td>0.081***</td>
<td>0.228***</td>
<td>0.108***</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Character</td>
<td>0.650</td>
<td>0.650</td>
<td>0.177***</td>
<td>0.162***</td>
<td>0.123***</td>
<td>-0.137***</td>
<td>0.181***</td>
<td>0.123***</td>
<td>0.313***</td>
<td>-0.211***</td>
<td>1</td>
</tr>
</tbody>
</table>

Tab. 3 reports the regression analysis results of the main effects of firm knowledge characteristics on technological innovation. The baseline model estimates the impact of control variables on firm innovation. The regression results indicate that firm patent accumulation ($β=0.117$, $p<0.01$) and firm age ($β=-0.056$, $p<0.05$) have significant effects on incremental innovation.

Building upon the baseline model, Model 1 verifies a significant negative impact of knowledge diversity on radical innovation ($β=-0.010$, $p<0.01$), supporting H1. Model 2 confirms the promoting effect of knowledge diversity on incremental innovation ($β=0.010$, $p<0.01$), providing support for H2.

In Model 3, the coefficient of firm knowledge uniqueness is 0.001, and it is positively correlated with radical innovation at a 10% significance level, thus validating H3.
In Model 4, the coefficient of firm knowledge uniqueness is -0.005, and it is significantly negatively related to radical innovation at a 1% significance level, supporting H4.

### Table 3 - Regression results
(compiled by co-authors)

<table>
<thead>
<tr>
<th></th>
<th>Master Model</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exp1</td>
<td>Exp2</td>
<td>Exp1</td>
<td>Exp2</td>
<td>Exp1</td>
</tr>
<tr>
<td>Kdiv</td>
<td>-0.010***</td>
<td>0.010***</td>
<td>(-4.11)</td>
<td>(7.65)</td>
<td>0.001*</td>
</tr>
<tr>
<td>Kuni</td>
<td>0.018</td>
<td>0.117***</td>
<td>0.057**</td>
<td>0.081***</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
<td>(6.00)</td>
<td>(2.04)</td>
<td>(4.32)</td>
<td>(1.15)</td>
</tr>
<tr>
<td>Paccuin</td>
<td>-0.011</td>
<td>0.108**</td>
<td>-0.064</td>
<td>0.041</td>
<td>-0.062</td>
</tr>
<tr>
<td></td>
<td>(-2.55)</td>
<td>(0.08)</td>
<td>(-1.05)</td>
<td>(0.64)</td>
<td>(-3.10)</td>
</tr>
<tr>
<td>Character</td>
<td>0.042</td>
<td>-0.011</td>
<td>0.108**</td>
<td>-0.064</td>
<td>0.041</td>
</tr>
<tr>
<td>Year</td>
<td>(0.91)</td>
<td>(-0.25)</td>
<td>(2.24)</td>
<td>(-1.24)</td>
<td>(0.90)</td>
</tr>
<tr>
<td>GDP*ln</td>
<td>-0.017</td>
<td>-0.067</td>
<td>-0.079</td>
<td>0.028</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(-0.10)</td>
<td>(-0.42)</td>
<td>(-0.46)</td>
<td>(0.17)</td>
<td>(-0.07)</td>
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<td>Included</td>
<td>Included</td>
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<td>Included</td>
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<tr>
<td>_cons</td>
<td>0.325</td>
<td>3.028*</td>
<td>0.320</td>
<td>2.300</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(1.85)</td>
<td>(0.16)</td>
<td>(1.32)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Loglikelihood</td>
<td>-2407.1578</td>
<td>-2680.184</td>
<td>-2398.1436</td>
<td>-2405.5776</td>
<td>-2654.5658</td>
</tr>
<tr>
<td>Waldchi2</td>
<td>199.11</td>
<td>337.90</td>
<td>220.95</td>
<td>450.68</td>
<td>202.07</td>
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<tr>
<td>Prob</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: ***, **, and * represent significant at 1%, 5%, and 10% levels, respectively. N=1786/1759

**Robustness analyses**

To further validate the robustness of the empirical results, the dependent variables of firm breakthrough innovation and incremental innovation were adjusted by adding 1 and taking the natural logarithm as measurement.

The other model settings remained unchanged, and a fixed effects model using OLS regression was employed for the robustness analysis. The regression results are shown in Tab. 4, and the results are consistent with the previous findings, indicating the strong robustness of the results in this study.
## Table 4 - Analysis of fixed effect OLS regression results (compiled by co-authors)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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</thead>
<tbody>
<tr>
<td>Exp1</td>
<td></td>
<td></td>
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<tr>
<td>Exp2</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Kdiv</td>
<td>-0.014***</td>
<td>0.016***</td>
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<tr>
<td></td>
<td>(-7.17)</td>
<td>(10.73)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kuni</td>
<td>0.001***</td>
<td>0.002***</td>
<td></td>
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<tr>
<td></td>
<td>(2.68)</td>
<td>(-9.50)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paculln</td>
<td>0.022</td>
<td>0.082***</td>
<td>-0.002</td>
<td>0.092***</td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(4.94)</td>
<td>(-0.09)</td>
<td>(5.48)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.033</td>
<td>-0.205***</td>
<td>-0.148***</td>
<td>-0.076**</td>
</tr>
<tr>
<td></td>
<td>(-0.72)</td>
<td>(-5.59)</td>
<td>(-3.36)</td>
<td>(-2.19)</td>
</tr>
<tr>
<td>Scalsln</td>
<td>0.089</td>
<td>0.124***</td>
<td>0.061</td>
<td>0.144***</td>
</tr>
<tr>
<td></td>
<td>(1.57)</td>
<td>(2.75)</td>
<td>(1.05)</td>
<td>(3.17)</td>
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<td>GDPln</td>
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<td>-0.103</td>
<td>0.188</td>
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<td>(0.74)</td>
<td>(-0.34)</td>
<td>(0.49)</td>
<td>(0.15)</td>
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<tr>
<td>_cons</td>
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<td></td>
<td>(-0.54)</td>
<td>(-0.38)</td>
<td>(-0.21)</td>
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</tr>
<tr>
<td>F</td>
<td>24,502</td>
<td>32,823</td>
<td>20,913</td>
<td>30,753</td>
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<tr>
<td>R²</td>
<td>0.208</td>
<td>0.260</td>
<td>0.183</td>
<td>0.248</td>
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<tr>
<td>N</td>
<td>1917</td>
<td>1917</td>
<td>1917</td>
<td>1917</td>
</tr>
</tbody>
</table>

Note: ***, **, and * represent significant at 1%, 5%, and 10% levels, respectively. R² indicates within R²

### Conclusion and implications

**Conclusion**

In today's highly competitive market environment, the technological innovation capability of enterprises is crucial for their survival and development. In order to gain competitive advantage and innovation momentum, an increasing number of companies choose to join collaborative innovation networks, hoping to leverage this network structure to integrate various resources and facilitate technological innovation.

However, when enterprises engage in knowledge search within collaborative innovation networks, the impact of their own knowledge characteristics on technological innovation may vary.

1. The promotion effect of knowledge diversity on incremental innovation in enterprises.

Specifically, the diversity of knowledge within a company enables better integration of various resources and knowledge. By cooperating with members from different domains, such as computer science, mechanical engineering, and electronic engineering, a company can acquire knowledge from different technological fields.

These knowledge domains can complement and synergize with each other, resulting in new technological and product solutions. For instance, a high-tech company aiming to innovate in the field of autonomous driving may lack the requisite technical knowledge.
However, by collaborating with network members specializing in computer science, mechanical engineering, and electronic engineering within the collaborative innovation network, the company can effectively share knowledge and expertise, thereby integrating resources and enhancing its technological innovation capabilities to make its autonomous driving products more competitive.

(2) The promotion effect of knowledge distinctiveness on breakthrough innovation in enterprises. Specifically, knowledge distinctiveness enables a company to gain an advantage in market competition. In certain specific markets and domains, if a company possesses unique skills, resources, and specialized knowledge, it can establish a monopoly position and reap substantial returns. For example, a pharmaceutical company holding a new patented technology that significantly improves the production efficiency and quality of active pharmaceutical ingredients can leverage this technology in practical production and sales. As a result, the company can seize market advantages, garner more market share, and generate higher profits.

**Implications**

This study aims to delve into the relationship between the knowledge characteristics of enterprises in collaborative innovation networks and technological innovation. It proposes a multi-level network model and analyzes the boundary conditions of the impact of knowledge characteristics on innovation. In addition, it expands the scope of research in collaborative innovation theory. The potential theoretical contributions are as follows:

(1) expansion of theoretical research on enterprise innovation;
(2) enrichment of the structural characteristics of the knowledge base of enterprises and its impact on innovation; and
(3) development of a research perspective using multi-level network models.

The relationship between the knowledge characteristics of enterprises in collaborative innovation networks and technological innovation is a complex and significant issue. Modern enterprises, while expanding in scale and intensifying technological research and development, increasingly rely on collaborative innovation networks to jointly develop and launch new products, technologies, and services.

The conclusions of this thesis study suggest that the knowledge characteristics of enterprises have diverse effects on their technological innovation behavior. Based on these findings, insights for practical management are proposed, emphasizing the importance of continuously exploring the organization's own knowledge capabilities.

This includes examining the internal knowledge structure and reserves of the enterprise, as well as exploring employees' professional backgrounds and skills, in order to optimize the innovation environment. For example, enterprises can enhance their competitiveness and market share by cultivating internal talent, establishing and improving their knowledge management systems, and fostering knowledge sharing and innovation.

**Limitations and further study**

Although this study collected all the invention patent information in China's high-tech manufacturing industry up until the end of 2018, these patent data may not fully reflect the current development status of China's high-tech manufacturing industry.
Therefore, future research should update the data on patent inventions to test the robustness and effectiveness of the existing conclusions. In addition, this study included a sample of 515 companies from nearly 18 industries that met the requirements of being technology-intensive and having patented inventions.

Based on this, future research can further enrich and improve the theoretical framework of this study by conducting comparative analysis between high-tech industries and traditional industries in a specific industry sector and examining the differential impact mechanisms of firm knowledge characteristics on innovation activities.

References:


THE INFLUENCE OF FIRM KNOWLEDGE


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