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Research Article

The Effects of Knowledge Base Diversity on Cross-Industry Innovation Performance: The Moderating Role of Network Embeddedness

Yang Zhou, Chunyu Meng, and Xin Chen

Business School, University of Shanghai for Science and Technology, Shanghai 200093, China

Correspondence should be addressed to Xin Chen; ares0825@163.com

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To reveal the impact of knowledge base diversity (KBD) and network embeddedness on cross-industry innovation performance (CIP), we performed an empirical hierarchical regression analysis using patent data from the mobile phone industry. The results show the following. (1) There was an inverted U-shaped relationship between relevant KBD and CIP and a U-shaped relationship between nonrelevant KBD and CIP. (2) The effects of relevant KBD on CIP were negatively moderated by an enterprise's structural embeddedness (SE) and relational embeddedness (RE) in the innovation network. (3) The effects of nonrelevant KBD on CIP were positively moderated by an enterprise's SE and RE in the innovation network. The findings contribute to the body of knowledge on the influencing factors of CIP and provide guidance for cross-industry innovation practice.

1. Introduction

Innovation is an important source to maintain enterprises' competitive advantage [1]. With the rise of digital technology, the logic of innovation has undergone tremendous changes in recent years [2, 3]. More and more enterprises introduce digital technology into their business activities and attempt to achieve innovation across industry boundaries [4]. This phenomenon has been around since forever but has now become a hot topic, which can be classified as "cross-industry innovation" (i.e., the process of exploring and adapting the established technologies of one industry to develop innovative products in another) [5]. Specifically, the cross-industry innovation adopts the analogy method [6], focusing on the creative imitation of the existing solutions in other industries to meet the innovation needs of enterprises [7, 8], which may help enterprises to break through the development bottleneck, open new development space, and achieve sustainable growth [9]. However, not all innovations bear fruit in the end, and the outcome of innovation is simultaneously determined by the internal and external factors [10].

Among these factors, knowledge plays a critical role in driving innovation to success [11, 12]. The accumulation of knowledge can bring a better control and coordination to enterprise in the innovation process [13]. The existing empirical research demonstrates that knowledge base diversity (KBD) actually has a significant influence on the outcomes of innovation, and their relationship is often moderated by the enterprises' attributes, such as absorption ability and embeddedness in innovation network [14, 15]. For instance, Liu et al. proposed that in the process of technological innovation, relevant KBD has a significant positive impact on the improvement of innovation performance, while nonrelevant KBD shows an inverted U-shape impact on it [16]. Bierly and Chakrabarti used tissue absorption ability as a moderating variable and empirically confirmed the impact of breadth of knowledge base and depth of knowledge base on enterprise innovation performance under different innovation strategies [17]. Additionally, the enterprise usually cooperates with other external entities in an open innovation system, constructing the innovation network [18]. Ebers and Maurer found that the relationship with other external entities is an effective channel for the transmission of complex knowledge. The stronger the relationship, the more conducive the transmission of complex knowledge between enterprises, so as to promote enterprise innovation [19].

As a special case of innovation, cross-industry innovation often involves combinations of knowledge from various industries, and its performance should be influenced by KBD in theory. Moreover, given that the integration and utilization of cross-industry knowledge are constrained by the cognitive distance and barriers [9, 20] which is inherently related to KBD, the impact of KBD on the performance of cross-industry innovation may be more noteworthy. However, the existing literature provides limited empirical evidence, and only a few scholars explored the impact of the external knowledge and technology accumulation on CIP. For example, Ciliberti et al. found that the cross innovation in Italian food industry relies on different external knowledge sources, such as the external R&D activities, the acquisition of outside technology, and the information provided by suppliers and consultants [21]. Zhou et al. found that the technology spillovers perceived by enterprises positively influence CIP through a complex dynamic mechanism [22]. Zhang et al. investigated the impact of the difference degree between the new entrants' preentry technology accumulation and the technology of the targeted industry of entry on its subsequent CIP [23]. Despite the present research, we still know little about how the diversity of enterprises' knowledge base influences their CIP. Meanwhile, CIP is also achieved in an open innovation system [24]. The innovation network provides an innovation path for industries' integration [25]. This view affirms the impact of the innovation network in the process of enterprise innovation, but the relevant research on innovation network has not directly clarified the role of network embeddedness in cross-industry innovation. The disclosure ofthe influence mechanism of KBD and network embeddedness on CIP can provide enterprisewith reference on resource allocation and knowledge base construction. This willhelp enterprises improve their cross-industry innovation ability, gain a competitiveadvantage, and expand their market share.

In the transformation and upgrading of the manufacturing industry, China's manufacturing industry is in a critical period of transformation from labor-intensive low-end manufacturing to knowledge-intensive high-end manufacturing [26]. Enterprises urgently need to improve their own independent research and development capabilities. By crossing original industry boundaries, enterprises can deeply explore more technical possibilities. Then, enterprises can find innovation channels amid fierce market competition and integrate different product functions in the process of cross-industry innovation, bolstering the competitive edge of the product in the global market. In this context, our study aimed to deepen the understanding of the influencing factors of cross-industry innovation, help enterprises build a reasonable knowledge base, and maintain a good cooperative relationship with other innovation subjects to improve CIP. Therefore, this study constructed the relationship model between KBD and enterprise CIP and incorporated network embeddedness into the model to empirically investigate how the knowledge base and network embeddedness affect enterprise CIP.

The structure of the remainder of this paper is as follows. Section 2 describes and constructs the research framework for the relationship between the KBD, network embeddedness, and CIP. Based on theoretical foundations, research hypotheses are proposed. Section 3 presents the research design and methodology, including the sample selection, data collection, data processing, variable measurement, and methodology. Section 4 outlines the empirical testing process and discusses the empirical results. Section 5 provides the conclusions, implications, limitations, and future prospects of the study.

2. Theoretical Background and Hypotheses

2.1. KBD and CIP. By crossing the boundaries of the current industry, enterprises can integrate the advanced ideas and solutions of other industries into their own innovation. Then, they can break through the original technological track, redefine the industry rules, and reposition their products, including the products' function, performance, and scope of application, thus reforming their core competitive advantages [7]. In this process, if the knowledge base of an enterprise is multidimensional, covering the technology, knowledge, and innovation elements of many other industries, it may be easier for this enterprise to integrate and innovate, objectively facilitating its CIP. We selected the KBD to measure the diversity of an enterprise's knowledge base. Consistent with the division standard of Krafft, we divided KBD into two dimensions: relevant KBD and nonrelevant KBD [27], and we constructed the conceptual model based on this division.

2.1.1. Relevant KBD and CIP. Relevant KBD refers to the proportion of knowledge elements that belongs to the enterprise's own industry in relation to its total knowledge elements [16]. The level of an enterprise's relevant KBD is closely related to its resource allocation, knowledge heterogeneity, and willingness to pursue cross-industry innovation. Therefore, relevant KBD may affect CIP. First, a high level of relevant KBD means that an enterprise will allocate more resources to further improve and upgrade the existing technology. The outcomes of this resource allocation are more incremental innovations, rather than cross-industry innovations. The probability of cross-industry innovation will be greatly reduced [16]. Second, a higher relevant KBD indicates that the knowledge accumulated by the enterprise is limited to one or a few technical fields closely related to its own industry [28]. In this case, the enterprise lacks the accumulation of heterogeneous knowledge elements in other new technical fields, which is not conducive to cross-industry innovation. Third, when the enterprise maintains relevant KBD at a high level, it will generate a strong inertia that drives the enterprise to use the industry internal knowledge to pursue incremental innovation. This inertia will inhibit the willingness to search for knowledge outside the industry, which is not conducive to the enterprise conducting innovation activities across the industry boundary.

Still, it is not a good choice for enterprises to blindly pursue the reduction of relevant KBD to promote cross-industry innovation. On the contrary, with the continuous reduction of relevant KBD, cross-industry innovation may be inhibited. The technical advantage in the enterprise's original industry is a key success factor of cross-industry innovation [29]. When an enterprise's relevant KBD is at a low level, its familiarity, mastery, and the R&D ability of the relevant technologies in its own industry are also low [30]. Accordingly, the enterprise cannot fully exploit the technical advantages in its original industry when it engages in cross-industry innovation, which will result in the inhibition of the CIP. Moreover, when an enterprise pays little attention to the relevant technologies in its own industry, it can easily ignore the dynamic changes of the market and have difficulty accurately grasping the mainstream direction of cross-industry development, which will result in a low sensitivity to the new mainstream design brought by cross-industry innovation and the loss of cross-industry innovation opportunities.

Therefore, within a certain critical range, the higher the relevant KBD is, the more beneficial it is to CIP. However, when relevant KBD exceeds the critical point, higher relevant KBD inhibits CIP. Accordingly, we propose the hypothesis below.

> H1: an inverted U-shaped relationship exists between relevant KBD and CIP.

2.1.2. Nonrelevant KBD and CIP. Nonrelevant KBD refers to the proportion of resources allocated by the enterprise to nonrelevant technological fields [31]. Enterprises with a low degree of nonrelevant KBD are more inclined to seek innovation solutions from relevant technical fields of their own industry or neighboring industries. Seeking solutions in neighboring industries can help an enterprise acquire the diversified heterogeneous technology and knowledge needed in cross-industry innovation. Moreover, as a certain degree of similarity exists between the technology of neighboring industries and the enterprise's industry, the technologies of neighboring industries are more likely to substantively spill over to the enterprise [22], facilitating cross-industry innovation. However, limited by the information processing ability and the lack of experience in dealing with multiple kinds of knowledge, when faced with excessive nonrelated technologies, an enterprise may experience information overload [32], which will have a negative impact on CIP.

With the continuous increase of nonrelevant KBD, the enterprise will accumulate enough experience in processing heterogeneous information and knowledge, and its ability to deal with the information processing will be accordingly enhanced. When the level of nonrelevant KBD exceeds a certain critical point, the impact of nonrelevant KBD on CIP will turn from negative to positive. At this time, as the enterprise will have a stronger ability to absorb heterogeneous knowledge and information, the technology in the relatively far distant industries can also spill over to the enterprise [22]. This means that a high level of nonrelevant KBD can, to some extent, help enterprises to broaden the scope of technical resources they own [16], leading enterprises to have a large number of heterogeneous knowledge elements. In technological innovation, the arrangement and application of these heterogeneous knowledge elements can help improve product diversification [33] and increase the possibility of obtaining cross-industry innovation solutions. At the same time, when the level of nonrelevant KBD is high, the learning ability and efficiency of enterprises is also relatively high, which will greatly reduce the cost of technology search, internalization, and integration [34], eventually improving the performance of cross-industry innovation.

In sum, a nonlinear relationship exists between nonrelevant KBD and CIP. Before the level of nonrelevant KBD reaches the critical point, a higher level of nonrelevant KBD is detrimental to CIP. However, when nonrelevant KBD exceeds the critical point, the higher the nonrelevant KBD, the better the CIP. Therefore, we propose the hypothesis below.

> H2: a U-shaped relationship exists between nonrelevant KBD and CIP.

2.2. Network Embeddedness and CIP. According to the network embeddedness theory, by becoming embedded in a cooperation innovation network, an enterprise can establish a continuous, reciprocal network relationship with its partners, which can help the enterprise obtain innovation resources and can increase the likelihood of innovation success. One of the characteristics distinguishing cross-industry innovation from general innovations is that the former, to a greater extent, depends on the acquisition of technology and resources of other industries. The manner and the level of embeddedness in the cooperation innovation network will affect the acquisition of external resources and further impact CIP [34]. To reveal the impact mechanism of network embeddedness on CIP, we divided network embeddedness into two dimensions: structural embeddedness (SE) and relational embeddedness (RE).

2.2.1. SE and CIP. SE emphasizes the connection relationship structure between the enterprise and the other enterprises in the innovation network, as well as the position characteristics of the enterprise in the innovation network [18]. The level of network embeddedness is reflected in the opportunities for the enterprise to acquire and master information, technical knowledge, and other innovation resources from the network [35]. This is because as the level of network embeddedness increases, the status of enterprises in the network is also enhanced, which can provide enterprises with more opportunities to access heterogeneous resources and diversified information [34]. Enterprises can realize the integration of technologies and knowledge in different fields on the existing technological trajectory by cooperation or knowledge exchange with the enterprises connected to it in the innovation network, which may affect the relationship between the enterprises' KBD and CIP.

From the perspective of relevant KBD, SE will negatively moderate the impact of relevant KBD on CIP. An enterprise occupying a core position in the innovation network can master more knowledge elements and can engage in better management of its external technology resources [36]. Therefore, it is helpful for an enterprise to obtain technical support from the innovation network and compensate for its shortcomings in related technological fields when conducting cross-industry innovation. At the same time, close contact with the members in the innovation network can also help an enterprise grasp the technological development trends, which will negatively moderate the impact of relevant KBD on CIP. Moreover, a high level of SE helps an enterprise cooperate with other enterprises in the innovation network and gives it the opportunity to obtain the technology or knowledge of different technological tracks [37]. These traits can compensate for the lack of diversified knowledge elements in the enterprise and can weaken or even eliminate the influence of the homogenization of the knowledge base on CIP. Furthermore, a high level of SE can broaden the enterprise's focus to different industries [38], objectively providing a good environmental basis for enterprises to carry out cross-industry innovation.

From the perspective of nonrelevant KBD, a high level of SE will strengthen the impact of nonrelevant KBD on CIP. Enterprises located in the center of the innovation network and occupying more structural holes are more likely to capture market opportunities and grasp the development trends of the industry [39]. An enterprise with high SE can take advantage of its position in the network to obtain vast heterogeneous information resources, which is helpful to expand their cross-industry innovation thinking. Moreover, when the enterprise's SE is relatively high, it can engage in a deep cooperative relationship with other enterprises in the network, especially those from other industries. This deep cooperation usually means that the knowledge sharing among the enterprises is no longer limited to the explicit knowledge, but allows them to identify and utilize each other's tacit knowledge, which is conducive to improving the quality and efficiency of cross-industry innovation. Therefore, we propose the hypotheses below.

H3a: the effects of relevant KBD on CIP are negatively moderated by an enterprise's SE in the innovation network.

H3b: the effects of nonrelevant KBD on CIP are positively moderated by an enterprise's SE in the innovation network.

2.2.2. RE and CIP. RE reflects the relational features among the enterprise and the other enterprises in the innovation network, including the degree of familiarity and the level of information sharing in these relationships [40]. Among the most important reflections of RE is the frequency and depth of interorganizational connections, which determine whether the enterprise can build a trust relationship with other enterprises to acquire necessary innovation resources. The high level of RE implies that the enterprise can construct a relatively stable cooperative relationship. In such a situation, the enterprise will have a better understanding of which kind of knowledge reserves of its partners can be utilized, so when seeking knowledge resources from them, its purpose will be clearer and the redundancy will be lower [41]. Moreover, when the enterprise has a high level of RE in the innovation network, the frequent interactions between network partners can strengthen their dependence on each other. Collaborating with reliable partners can greatly reduce the costs and risks of cross-industry innovation. Therefore, RE can, to some extent, affect the relationship between the enterprise's KBD and its CIP.

From the perspective of relevant KBD, a higher level of RE weakens the impact of relevant KBD on CIP. When the enterprise's RE level is relatively high, it can obtain more novel, valuable, and diverse tacit knowledge and other resources from the innovation network through strong connections [42], which will compensate for the shortcomings of the high homogeneity of the enterprise's own knowledge base. Moreover, RE emphasizes the establishment of trust and reciprocal relationships between the enterprise and other nodes in the innovation network through long-term interaction, cooperation, or transactions [43], which enhances the enterprises' willingness to share information or collaborate on innovation [44]. Furthermore, this will promote the transfer of innovative resources and knowledge between network node enterprises, making it easier for enterprises to acquire heterogeneous knowledge and reducing the impact of highly relevant KBD.

However, from the perspective of nonrelevant KBD, a high level of RE will strengthen the impact of nonrelevant KBD on CIP. Maintaining strong connections with other enterprises in the innovation network can bring more learning opportunities to enterprises, and enterprises can achieve cooperation and knowledge exchange through intentional knowledge spillover behavior, thereby expanding their knowledge acquisition channels [45]. In addition, good network relationships are beneficial for the enterprise to engage in deep communication and exchange with other enterprises and to improve its information processing and integration capabilities. This will strengthen the relationship between the enterprise's nonrelevant KBD and its CIP. Therefore, we propose the hypotheses below.

H4a: the effects of relevant KBD on CIP are negatively moderated by an enterprise's RE in the innovation network.

H4b: the effects of nonrelevant KBD on CIP are positively moderated by an enterprise's RE in the innovation network.

In summary, based on the above analysis, we established the conceptual model shown in Figure 1.

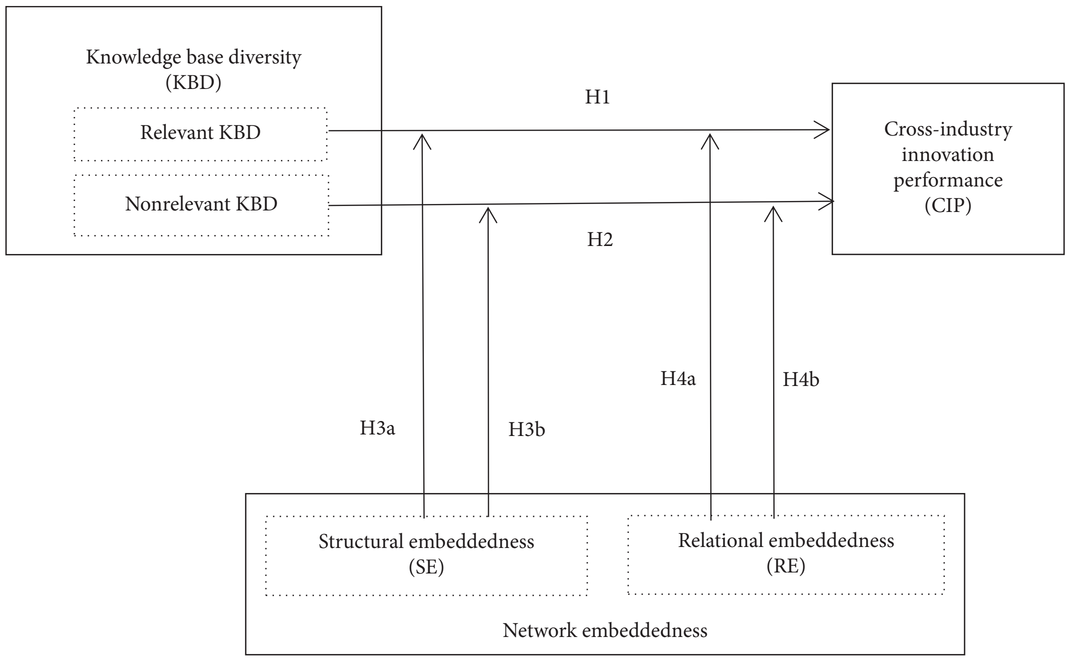

Figure 1: Conceptual model.

3. Research Design and Methodology

3.1. Sample Selection and Data Sources. The research setting of this study was the mobile phone industry, mainly for two reasons. First, the mobile phone industry has obvious characteristics of cross-industry innovation. In the past, the mobile phone industry has integrated the technologies from serval traditional industries by cross-industry innovation. For example, it integrated the technology of the digital camera industry and realized the camera function. In another instance, it integrated the technology of the touch screen industry and realized touchable and operable screen functions. In recent years, with the mobile phone industry entering a higher stage of technological development, communication and collaboration between the main participants in technical cooperation have become more frequent, facilitating more cross-industry innovations. Therefore, the mobile phone industry provides us a substantial data source for undertaking empirical research. Second, the mobile phone industry occupies a vital position in the national economy. Especially in the 5G era, the mobile phone industry has a broad and far-reaching impact on the economy and society. Therefore, it is of great significance to conduct in-depth research on the cross-industry innovation and its antecedents of the mobile phone industry.

We collected patent data of the mobile phone industry from the Derwent Innovations Index to test our hypotheses. Considering the development process of the mobile phone industry, we set the patent publication date range from January 1, 2011, to December 31, 2020. The query condition was "TS = Cell Phone or Cellular Phone or Mobile Phone or Smartphone or Smart Phone." In the mobile phone industry, a large number of patentees exist. However, the distribution of patentees who rank low in the number of patents is relatively scattered, and the number of patents is in a significant decline. By referring to the general method of existing studies [18], we retained patentees in the top 50% of the patent number ranking in the mobile phone industry from 2009 to 2021 (2009 was the first year when smartphones began to become popular, and 2021 was the latest year for the complete year-round data available for retrieval). A total of 275,378 pieces of patent data were obtained as panel data sources. The search and collection of all patent data were completed on November 10, 2022.

3.2. Data Processing. We organized the collected raw patent data before the data analysis. Because most of the patented technologies rapidly lose their technological value within approximately 5 years and no longer have market competitiveness, a 5-year moving window is the most appropriate time frame for evaluating the impact of technologies [43]. This processing method can also effectively reduce the annual fluctuations, thereby making the indicators more accurate in reflecting the enterprise's patent application tendency [46]. Adopting the method of Achilladelis et al. [46], we processed the patent data based on a 5-year moving window. When calculating variables, we used the patents obtained by the patentee from year $t-5$ to year $t-1$ to represent its patents in year t.

Then, we classified the patents based on the International Technical Classification (IPC) [16]. First, we extracted the IPCs of each patent. The first four digits of IPC represent the technology subcategory to which the patent belongs, based on which we classified each patent into different technology subcategories and calculated the number of each patentee's patents that belongs to technology subcategory i in year t, recorded as M_{it}. The first capital letter of IPC represents the technology category to which the patent belongs, based on which we classified each patent into different technology categories and calculated the number of each patentee's patents that belongs to technology category j in year t, recorded as N_{jt}. Based on M_{it} and N_{jt}, we continued to calculate the proportion of the patents classified as technology subcategory i and technology category j in the total in year t, recorded as P_{it} and P_{jt}, and we calculated relevant KBD and nonrelevant KBD of each patentee with the Stata software.

Next, we extracted the patent citation information of all patentees and constructed a "90×90" adjacency matrix based on the mutual citation among patentees. In the adjacency matrix, the data in the row i and column j represent the times that patentee i is cited by the patentee j. Then, we binarized the constructed adjacency matrix to obtain a 0-1 matrix. Based on the 0-1 matrix, we calculated the SE and RE of each patentee with UCINET software.

Finally, we calculated the quantity of cross-industry IPCs of each patentee, taking the concordance table between the IPC and the International Standard Industrial Classification (ISIC—rev. 2) as the base for dividing industries [47]. According to the concordance table, all of the IPCs were classified into 25 industries. The first (Electric mach., ex. electronics) and second ones (Electronics) are closely related to the early technologies involved in the mobile phone and can be considered as the original industry of mobile phone. Therefore, we deducted the IPCs belonging to these two categories from the total and obtained the number of cross-industry IPCs of patentee i in year t, recorded as k_{it}. We further calculated the variable of CIP based on k_{it} with Stata.

3.3. Variable Measurement

3.3.1. KBD. We divided KBD into relevant KBD and nonrelevant KBD. Referring to the studies of Liu et al. [16] and Chen and Chang [48], we used the information entropy index to measure KBD. The calculation formula is as follows:

$$\mathrm{KBD}_t = \sum_{i=1}^{n} P_{\mathrm{it}} \ln\left(\frac{1}{P_{\mathrm{it}}}\right), \tag{1}$$

where KBD_t is the enterprise's KBD in the year t, P_{it} is the proportion of patents belonging to technology subcategory i in its total patents in the year t, and n is the total number of technology subcategories.

$$\mathrm{NKBD}_t = \sum_{j=1}^{n=8} P_{\mathrm{jt}} \ln\left(\frac{1}{P_{\mathrm{jt}}}\right). \tag{2}$$

In equation (2), NKBD_t is the enterprise's nonrelevant KBD in the year t, and P_{jt} is the proportion of patents belonging to technology category j in its total patents in the year t. There are eight total technology categories.

$$\mathrm{RKBD}_t = \mathrm{KBD}_t - \mathrm{NKBD}_t. \tag{3}$$

In equation (3), RKBD_t is the enterprise's relevant KBD in year t.

3.3.2. Network Embeddedness. We divided network embeddedness into two dimensions: SE and RE. Referring to the study of Mazzola et al. [49], we used the structural hole index (i.e., the number of structural holes occupied by the patentee in the innovation network) to measure the patentee's SE. The effective size of the network was used to measure the structural holes in this calculation, reflecting nonredundancy [42]. The formula is as follows:

$$\begin{aligned}\mathrm{SE}_i &= \mathrm{SH}_i \\ &= \sum_j \left(1 - \sum_q p_{\mathrm{iq}} m_{\mathrm{jq}}\right), \quad q \neq i, j,\end{aligned} \tag{4}$$

where SE_i is the SE index of the patentee i. SH_i is the structural hole index of the patentee i. j is the patentee directly connected to patentee i. q is the third-party patentee except patentee i and patentee j. $p_{iq}m_{jq}$ is the redundancy between patentee i and patentee j. As for the RE, it is reflected by the number of connections between the patentee and other patentees in the innovation network [40]. Specifically, the level of RE within the innovation network is measured by calculating the sum of the out-degree and the in-degree of target nodes [18, 50].

By inputting the "90×90" 0-1 matrix obtained from the data processing part into the software of UCINET, we obtained the structural hole index and centrality of each patentee in the innovation network in the year t (i.e., the SE and the RE).

3.3.3. CIP. Considering the influence of the magnitude of the data on the readability of results, we used the weighted number of cross-industry IPCs as the measurement of CIP. The formula is as follows:

$$\mathrm{CIP}_t = \frac{k_{\mathrm{it}}}{\mathrm{Total}}, \tag{5}$$

where CIP_t is the CIP of the patentee in the year t. k_{it} is the number of cross-industry IPCs of the patentee i in the year t. Total is the total number of cross-industry IPCs of all the patentees.

3.3.4. Control Variables. To reduce the interference of other factors on the results, we introduced the knowledge scale (KS) and knowledge breadth (KB) of the enterprise as control variables. KS refers to the enterprise's existing technological achievement stock [51]. It will have a certain impact on the enterprise's technological innovation performance. KB refers to the amount of technology categories to which the enterprise's knowledge elements belong. The more technology categories an enterprise is involved in, the more candidate solutions an enterprise has to choose from, which will have an impact on its innovation activities. Therefore, we introduced KS as a control variable and measured it by the total number of the enterprise's patents.

Also, we introduced KB as the control variable and measured it by the total number of all technology categories covered by the enterprise's patents.

3.4. Methodology. This study used hierarchical regression analysis to examine the relationship between variables. Hierarchical regression is a statistical method that explores differences among multiple regression models, especially when investigating mediation or moderation effects. It offers advantages over traditional regression methods by considering factors at different levels and providing a more comprehensive understanding of the impact of independent variables on dependent variables. It also helps us achieve more accurate and comprehensive discoveries in the relevant research field. The research focused on the mobile phone industry and utilized the quantity of patents applied by major patentees and the frequency of patent citation from 2011 to 2020 as research samples. The relevant KBD and nonrelevant KBD were empirically analyzed in terms of their direct impacts and joint impacts with network embeddedness. The specific models were as follows.

Model 1 regressed the control variable against the CIP, observing the direct effect of the control variable on the CIP without the influence of other variables. The regression equation is

$$\mathrm{CIP} = \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \varepsilon. \tag{6}$$

Based on Model 1, Model 2 included the knowledge basis as explanatory variables in the regression model, observing the direct role of the explanatory variables on CIP. The regression equation is

$$\mathrm{CIP} = \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{RKBD} + \beta_2 \mathrm{RKBD}^2 + \beta_3 \mathrm{NKBD} + \beta_4 \mathrm{NKBD}^2 + \varepsilon. \tag{7}$$

Model 3 included the moderating variable in the regression model based on Model 2, which can directly reflect the role of the moderating variable on CIP. The regression equation is

$$\mathrm{CIP} = \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{RKBD} + \beta_2 \mathrm{RKBD}^2 + \beta_3 \mathrm{NKBD} + \beta_4 \mathrm{NKBD}^2 + \delta_1 \mathrm{SE} + \delta_2 \mathrm{RE} + \varepsilon. \tag{8}$$

Model 4 and Model 5 included the interaction term of SE and explanatory variables into the regression model to observe the moderating role of SE. The regression equation is

$$\begin{aligned} \mathrm{CIP} &= \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{RKBD} + \beta_2 RKBD^2 + \eta_1 \mathrm{SE} + \eta_2 \mathrm{SE} \times \mathrm{RKBD} + \eta_3 \mathrm{SE} \times RKBD^2 + \varepsilon, \\ \mathrm{CIP} &= \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{NKBD} + \beta_2 \mathrm{NKBD}^2 + \eta_1 \mathrm{SE} + \eta_2 \mathrm{SE} \times \mathrm{NKBD} + \eta_3 \mathrm{SE} \times \mathrm{NKBD}^2 + \varepsilon. \end{aligned} \tag{9}$$

Models 6 and 7 included the interaction terms of RE and explanatory variables in the regression model to observe the moderating effect of RE. The regression equation is

$$\begin{aligned} \mathrm{CIP} &= \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{RKBD} + \beta_2 \mathrm{RKBD}^2 + \eta_1 \mathrm{RE} + \eta_2 \mathrm{RE} \times \mathrm{RKBD} + \eta_3 \mathrm{RE} \times \mathrm{RKBD}^2 + \varepsilon, \\ \mathrm{CIP} &= \alpha_1 \mathrm{KS} + \alpha_2 \mathrm{KB} + \beta_1 \mathrm{NKBD} + \beta_2 \mathrm{NKBD}^2 + \eta_1 \mathrm{RE} + \eta_2 \mathrm{RE} \times \mathrm{NKBD} + \eta_3 \mathrm{RE} \times \mathrm{NKBD}^2 + \varepsilon. \end{aligned} \tag{10}$$

4. Empirical Analysis

4.1. Descriptive Statistical Analysis. To enhance the comparability and interpretability of data, we performed dimensionless treatment on SE and RE. Table 1 lists the results of the mean, standard deviation, and correlation coefficient of each variable. To further test the possible multicollinearity between independent variables, we conducted a variance inflation test (VIF test). The results of the VIF test show that the tolerance of all variables was greater than 0.2 and that the

Table 1: Mean, standard deviation, and correlation coefficient of each variable.

Variable	Mean	Std. Dev.	CIP	KS	KB	RKBD	NKBD	SE	RE
CIP	0.30	0.18	1.00						
KS	0.12	0.04	−0.03	1.00					
KB	0.12	0.02	0.09	0.85*	1.00				
RKBD	2.03	0.48	0.66*	0.03	0.12*	1.00			
NKBD	1.00	0.33	0.75*	0.01	0.12*	0.68*	1.00		
SE	0.53	0.20	−0.07	0.11	0.08	0.38*	0.21*	1.00	
RE	0.70	0.21	−0.13*	0.36*	0.28*	0.30*	0.11	0.88*	1.00

*suggests that correlation coefficients have significant association at 10% (2-tailed).

VIF was less than 10. Thus, no multicollinearity existed between variables.

4.2. Regression Analysis. The hypotheses were tested by a hierarchical regression test. Before the hierarchical regression analysis, the logarithm of the data was taken to eliminate the possible heteroscedasticity problem. The results of hierarchical regression are shown in Table 2. The significance level refers to the determination of a small probability criterion that can be allowed as the judgment boundary in advance when conducting hypothesis testing. In this study, we selected a significance level of 10%. When the p value of the regression coefficient was less than 0.1, we considered the regression result to be significant.

The results of Model 1 show that KB had positive impacts on CIP ($\beta = 0.77$, $p < 0.01$), while KS had a negative impact on CIP ($\beta = -0.34$, $p < 0.01$).

The results of Model 2 show that when relevant KBD and nonrelevant KBD were introduced into the model, the model's ability to explain changes in dependent variables improved ($\Delta R^2 = 0.17$). A significant inverted U-shaped relationship was observed between relevant KBD and CIP ($\beta = -0.18$, $p < 0.05$). This result indicates that if an enterprise's relevant KBD is at a relatively low level, the influence of relevant KBD on CIP will be positive; if the enterprise's relevant KBD exceeds a certain critical level, the influence of relevant KBD will become negative. On the contrary, a U-shaped relationship was found between nonrelevant KBD and CIP ($\beta = 0.41$, $p < 0.01$). Thus, when the level of nonrelevant KBD is lower than the certain critical level, the influence of nonrelevant KBD on CIP will be negative; when the nonrelevant KBD is higher than the level, the nonrelevant KBD's influence on CIP will become positive, supporting hypotheses H1 and H2.

Then, we added the moderating variable, SE, into the model. The results are shown in Models 4 and 5. In Model 4, the product term of SE and the square of relevant KBD had a significant positive correlation with CIP ($\beta = 0.30$, $p < 0.01$). Before adding SE, an inverted U-shaped relationship was observed between relevant KBD and CIP. This indicates that the addition of SE in the model can negatively moderate the relationship between relevant KBD and CIP, supporting hypothesis H3a. In Model 5, the product term of SE and the square of nonrelevant KBD had a significant positive correlation with CIP ($\beta = 0.22$, $p < 0.1$). Before adding SE, a U-shaped relationship was found between nonrelevant KBD and CIP. The result indicates that the addition of SE in the model can positively moderate the relationship between nonrelevant KBD and CIP, supporting hypothesis H3b.

Last, we added the moderating variable, RE, into the model. The results are shown in Models 6 and 7. According to the results of Model 6, the product term of RE and the square of relevant KBD had a significant positive impact on CIP ($\beta = 0.45$, $p < 0.01$). Before adding RE, an inverted U-shaped relationship was observed between relevant KBD and CIP. The result indicates that the addition of RE in the model can negatively moderate the relationship between relevant KBD and CIP, supporting hypothesis H4a. In Model 7, the product term of RE and the square of nonrelevant KBD had a significant positive impact on CIP ($\beta = 0.35$, $p < 0.05$). Before adding RE, a U-shaped relationship was found between nonrelevant KBD and CIP. The result indicates that the addition of RE in the model can positively moderate the relationship between nonrelevant KBD and CIP, supporting hypothesis H4b.

4.3. Robustness Test. To continue to test the robustness of the above regression results, we refiltered the sample and conducted the regression analysis again with the new sample. The specific steps were as follows. Among the 90 previously selected patentees, we randomly excluded 15% of them and obtained a new sample set consisting of the panel data of 77 patentees. In the results of the new regression, shown in Table 3, the relationships and their significance between the variables are consistent with those in the original regression results, indicating that the results are robust and that the corresponding hypotheses can still be supported.

4.4. Discussion. By analyzing theories related to cross-industry innovation, knowledge base, and network embeddedness, we proposed four research hypotheses and empirically tested their validity.

Regarding H1, we explored the relationship between KBD and CIP. The research findings suggest an inverted U-shaped relationship between relevant KBD and CIP. The result partially confirms the viewpoint proposed by Liu et al. that the level of relevant KBD has a significant positive impact on its technological innovation performance [16]. However, owing to the unique characteristics of cross-

Table 2: Hierarchical regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
KS	−0.34***	−0.14***	−0.15***	−0.24***	−0.22***	−0.27***	−0.22***
KB	0.77***	0.18**	0.17**	0.44***	0.44***	0.43***	0.45***
RKBD		0.83***	0.87***	0.64***		0.64***	
RKBD^2		−0.18**	−0.17*	0.33**		0.34*	
NKBD		0.86***	0.82***		0.84***		0.86***
NKBD^2		0.41***	0.40***		0.39***		0.35***
SE			−0.07**	−0.13***	−0.06*		
RE			0.09*			−0.04	−0.05
SE*RKBD				−0.07			
SE*RKBD^2				0.30***			
SE*NKBD					0.03		
SE*NKBD^2					0.22*		
RE*RKBD						−0.07	
RE*RKBD^2						0.45***	
RE*NKBD							0.12*
RE*NKBD^2							0.35**
R^2	0.41	0.58	0.59	0.50	0.53	0.51	0.54
F	44.18	55.12	47.17	36.1	41.76	37.54	42.06

***, **, and *suggest that the parameter estimates are significant at 1%, 5%, and 10%, respectively.

Table 3: Robustness test.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
KS	−0.36***	−0.16***	−0.16***	−0.25***	−0.24 ***	−0.29***	−0.26***
KB	0.77***	0.20**	0.18**	0.44***	0.49***	0.45***	0.50***
RKBD		0.80***	0.84***	0.63***		0.61**	
RKBD^2		−0.20**	−0.19*	0.29*		0.35*	
NKBD		0.79***	0.74***		0.73***		0.75***
NKBD^2		0.35***	0.34***		0.36**		0.33***
SE			−0.08**	−0.12***	−0.06*		
RE			0.10*			−0.06	−0.03
SE*RKBD				−0.07			
SE*RKBD^2				0.30***			
SE*NKBD					0.04		
SE*NKBD^2					0.27**		
RE*RKBD						−0.03	
RE*RKBD^2						0.56***	
RE*NKVD							0.22**
RE*NKBD^2							0.53***
R^2	0.41	0.55	0.56	0.49	0.51	0.51	0.51
F	37.12	42.08	36.03	29.76	32.23	32.29	32.71

***, **, and *suggest that the parameter estimates are significant at 1%, 5%, and 10%, respectively.

industry innovation, it requires relevant technological resources from the same industry and the integration and use of innovative resources such as knowledge and technology in other industries. Therefore, excessively high relevant KBD can have a certain negative impact on CIP. This result is consistent with the perspective proposed by Krafft et al. that the higher the level of relevant KBD, the lower the possibility of technological innovation in completely new technological fields [27]. This finding further supports the positive impact of the knowledge base on CIP while reminding us that excessive knowledge relevance may limit the development of CIP.

Regarding H2, the research results indicate a positive U-shaped relationship between the level of nonrelevant KBD and CIP. This result partially aligns with the viewpoint of Mahnken and Moehrle that the combination of knowledge and technology from different fields leads to a continuous increase in the number of patents crossing traditional industry boundaries [52], but it is not entirely consistent. In this study, a clear negative correlation was observed between the level of nonrelevant KBD and CIP in the early stage of its continuous increase. The emergence of this negative correlation may be related to the knowledge integration ability and knowledge application ability of enterprises. Xie and

Zuo proposed that the higher the enterprise's knowledge absorption capability is, the more capable the enterprise is of identifying and utilizing beneficial external information [53]. Chen proposed that the enterprise's knowledge utilization capability can effectively transform various knowledge that the enterprise possesses into competitive advantages, ultimately improving the enterprise's performance [54]. Therefore, when the enterprise's knowledge integration ability and knowledge application ability are insufficient, even if the enterprise has a high level of nonrelevant KBD, it will be difficult for enterprises to integrate and use a large amount of heterogeneous knowledge. In addition, excessive knowledge redundancy will produce high maintenance costs and a waste of resources [55]. The time cost and opportunity cost of enterprises are too high, which can, to some extent, hinder the development of CIP. With the absorption of a large amount of heterogeneous knowledge by enterprises, the knowledge integration ability and knowledge utilization ability of enterprises will be continuously strengthened. When enterprises have the ability to deal with these elements of knowledge well, this obstacle to cross-industry innovation will gradually disappear. With the increase of nonrelevant KBD, the richer the industries involved in enterprises, the more conducive the output of cross-industry innovation. Therefore, there is a positive U-shaped relationship between the nonrelevant KBD and CIP.

In H3 and H4, we also explored the moderating effects of network embeddedness. SE emphasizes the positional characteristics of the technical entity in the network, while RE reflects the degree of information sharing between the enterprise and other technical entities. Both can affect the possibility of the enterprise acquiring diverse knowledge resources from the external environment, thereby playing a role in the innovation process of the enterprise. The research findings indicate that SE has a negative moderating effect on the relationship between relevant KBD and CIP, and that it has a positive moderating effect on the relationship between nonrelevant KBD and CIP. Thus, enterprises can weaken the adverse impact of excessive relevant KBD on CIP by increasing the level of SE. Additionally, improving the level of SE enables nonrelevant KBD to more fully play its role in promoting CIP. This is related to the knowledge resources that enterprises acquire from external innovation networks. The survey results of Zhang show that SE could facilitate the continuous inflow of external knowledge resources into the organization, thereby enhancing innovation performance [56]. The research results of this study further affirm the above conclusion. At the same time, RE also has a similar moderating effect on the relationship between relevant KBD and CIP. Strengthening the level of RE, enhancing the frequency and depth of contact between organizations, and maintaining stable partnerships can enable enterprises to obtain more abundant and diverse hidden knowledge resources in the innovation network. Thus, the impact of relevant KBD on CIP will be weakened, and the impact of nonrelevant KBD on CIP will be enhanced. This view is consistent with the study of Ebers and Maurer and the study of Wei and Deng, which suggested that stronger relationships are more conducive to the transfer of complex knowledge between firms and that the relationship strength positively affects organizational learning ability and corporate innovation [19, 57].

5. Conclusions, Implications, and Limitations

5.1. Conclusions. To further clarify the influencing factors of the performance of cross-industry innovation (CIP), we investigated how a knowledge base (i.e., relevant KBD and nonrelevant KBD), as well as network embeddedness (i.e., SE and RE), impacts CIP. The hierarchical regression analysis results showed that an inverted U-shaped relationship exists between relevant KBD and CIP; a U-shaped relationship exists between nonrelevant KBD and CIP; SE and RE negatively moderate the relationship between relevant KBD and CIP and positively moderate the relationship between nonrelevant KBD and CIP.

5.2. Theoretical Implications. First, this paper expanded on the theoretical understanding of the antecedents of cross-industry innovation by exploring the relationship between KBD and CIP. Knowledge provides vital support for enterprises' innovation activities. The knowledge base of enterprises inevitably affects their innovation performance. However, existing studies have generally focused on investigating the impacts of knowledge barriers [20], regional learning conditions [58], interindustry technology transfers [59], and absorptive capacity [60] on cross-industry innovation, without answering how the knowledge base impacts CIP? From this perspective, based on the view that KBD affects enterprise innovation performance, we further revealed the mechanism through which KBD affects CIP. Our findings are a further development of the above view. These new findings also support points proposed by Krafft et al. [27]. Therefore, the conclusion of this research further enriches and expands the theoretical research of cross-industry innovation.

Second, this paper revealed the nonlinear relationship between KBD and CIP and provided an explanation for this relationship by distinguishing relevant KBD and the nonrelevant KBD. We found an inverted U-shaped relationship between relevant KBD and CIP and a U-shaped relationship between the nonrelevant KBD and CIP. The division of KBD is consistent with the findings of Krafft and Liu [27, 61]. Moreover, the results of this paper show that in the context of cross-industry innovation, compared with treating KBD as one variable, distinguishing the different types of KBD yields more theoretical insights. The findings can open up the black box between KBD and CIP.

Finally, from the perspective of innovation network, this paper introduced the network embeddedness and revealed the moderating effects of SE and RE on the relationship between KBD and CIP. It is found that in cross-industry innovation, SE and RE serve as moderating variable to weaken the inverted U-shaped impact of relevant KBD on CIP and enhance the U-shaped impact role of nonrelevant KBD on CIP. Existing studies have proved that network embeddedness has an impact on the enterprise's innovation performance or innovation capability. The findings in this paper are an extension of existing studies in the cross-industry innovation context. Owing to the particularity of cross-industry innovation, enterprises need the knowledge elements of different industries to support cross-industry innovation activities. Enterprises are embedded in the innovation network and obtain the required heterogeneous knowledge from it, thereby moderating the impact of KBD on CIP.

5.3. Practical Implications. To improve the CIP of enterprises, based on our results, we propose three actions of practical significance for enterprises. First, the knowledge of the enterprises' own industry is the basis of innovations. The enterprises should pay attention to the absorption and accumulation of the knowledge in its industry. However, due to the unique nature of cross-industry innovation, excessively high relevant KBD can have a detrimental impact on CIP. Therefore, it is crucial for enterprises to maintain a moderate level of relevant KBD. This entails not neglecting the technical elements within their own industry while also expanding their knowledge reservoir beyond the confines of their industry, thus facilitating high levels of CIP. Second, heterogeneous knowledge elements can provide enterprises with multiple combinations of innovation solutions, which is an important support for enterprises to carry out cross-industry innovations. Enterprises should widely absorb external knowledge based on their own R&D needs and maintain a high level of nonrelevant KBD. Certainly, prior to that, enterprises also need to continuously enhance their ability to effectively integrate and utilize various knowledge elements, in order to avoid the excessive consumption of resources caused by a large amount of heterogeneous knowledge. Third, the positioning and relationships of enterprises within innovation networks will significantly impact their ability to access heterogeneous knowledge resources. Enterprises should strive to maintain strong cooperative relationships with other technological entities within the innovation network, while also securing advantageous positions. This will enable them to fully leverage the positive effects of SE and RE, adding sources of heterogeneous knowledge elements and ultimately promoting CIP.

5.4. Limitations and Future Prospects. This study had some limitations, which can be further investigated in the future. First, the KBD and innovation performance variables in this study were measured only with patent data. Although patent data have the advantage of objectivity, they cannot fully reflect the overall knowledge management and innovation activities of the enterprise. In the future, researchers can continue to collect more data from other sources such as questionnaires to further test the hypotheses, supporting the conclusions by multiple sources of evidence. Second, our conclusions are limited to the mobile phone industry. Whether these conclusions are equally valid in other industries has not been confirmed. Future research can investigate other industries to strengthen the universality or reveal the specificity of the conclusions in this paper. Third, the characteristics of different stages in the industry development process were not considered. Future research can continue to explore the dynamic impact of KBD on CIP in different industry development stages from the dynamic process perspective. Furthermore, digital transformation is gradually becoming a focal point in recent years. The combination between traditional industry and digital technology would not only trigger more and more cross-industry innovations but also bring new cross-industry innovation modes. Thus, future research should pay attention to the transformation of CIP model and focus the changes on the role of KBD.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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