Research Article

Technology Spillover Perception and Knowledge Network Trap in Cross-Industry Innovation: An Empirical Examination from Unmanned Aerial Vehicle (UAV)

Yang Zhou, Xin Chen, and Jianjia He

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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Cross-industry technology spillover perception (CTSP) refers to the degree to which the enterprise absorbs the technology spilling from outside industries. How does the enterprise’s CTSP impact its cross-industry innovation performance? To answer this question, we distinguished CTSP into CTSP-Width and CTSP-Depth and investigate their dynamical impacts on the cross-industry innovation performance from the perspective of industry development process. Furthermore, we also explored the impact of the enterprise’s knowledge flow in the innovation knowledge network on the above relationships. We conducted the hierarchical regression analysis based on patent data in UAV industry from 2006 to 2020. The results showed that (1) in the flat period of industry development, only CTSP-Width has a direct positive impact on cross-industry innovation performance. (2) In the low-speed climbing period and the high-speed growing period, the impact of CTSP-Width disappears, and the direct positive impact of CTSP-Depth appears. (3) In the flat period, both the moderator roles of knowledge contribution and knowledge proﬁtability are not signiﬁcant. In the low-speed climbing period, only knowledge proﬁtability plays the negative moderator role, while in the high-speed growing period, both the knowledge contribution and knowledge proﬁtability play significant negative moderator roles. This suggests that, when the industry develops into maturity, the negative moderation effect of knowledge network gradually appears, which indicates that there is a knowledge network trap.

1. Introduction

Cross-industry innovation means that the enterprises absorb the knowledge, technology, and other elements of outside industries into their own, as well as transferring their own internalized technologies or patents to outside industries [1, 2]. In cross-industry innovation, it is common to see that the technological achievements of one industry have a substantial impact on the production of other industries, which is called cross-industry technology spillover [3]. Existing studies have investigated the identification [4] and measurement [5] of cross-industry technology spillover. Enterprises’ perception of cross-industry technology spillover differentiates from each other [6], which may further impact on the outside-in process [7] and inside-out process [8] of cross-industry innovation. However, we still know little about how the enterprises’ cross-industry technology spillover perceptions influence their cross-industry innovation performance.

Besides, to follow the knowledge flow in cross-industry innovation, the innovation network perspective was deployed to existing studies. Referring to the theory of network structural holes, the occupier of structural holes in innovation knowledge network can obtain information advantage from network participants [9], which is conducive to improving innovation performance [10]. The studies on organizational inertia pointed out that enterprises’ important position in the innovation knowledge network means strong path dependence, which would ensure the effective source of external technical resources [11], however, may also hinder the effectiveness of diversified technical knowledge utilization [12, 13], thus affecting the cross-industry
innovation performance. The studies on knowledge absorptive capacity found that some enterprises have high knowledge absorptive capacity, but they still have difficulties to seize the opportunities of cross-industry innovation [14]. It can be seen that the openness of enterprises in the innovation network is the key factor affecting cross-industry innovation performance and may play a moderating role in the relationship between cross-industry technology spillover perception and cross-industry innovation performance. However, there is a lack of empirical research that can reveal the influence mechanism between the three.

When innovation network and openness are taken into consideration, it is necessary to deploy a dynamic process perspective to study the cross-industry innovation [15]. Existing studies have empirically verified that several antecedent variables, e.g., innovation openness [16] and entrant preentry technological backgrounds [15], dynamically influence on cross-industry innovation along with the industries’ development. We divided industry development into three periods according to the technology developing status and conducted the hierarchical regression analysis at different periods based the patent data of the main enterprises in UAV industry from 2006 to 2020. We aimed to contribute to the theory and practice of cross-industry innovation by providing the empirical and dynamic explanation on the influence mechanism of cross-industry technology spillover perception and knowledge network on cross-industry innovation performance.

The paper is organized as follows: firstly, based on the existing theories and literature, the hypotheses of the direct impacts and indirect moderator effects among cross-industry technology spillover perception, knowledge flow, and cross-industry innovation performance are put forward. Secondly, the hierarchical regression analysis is carried out based on the patent data of main enterprises in UAV industry. Finally, the empirical results are discussed.

2. Theory and Hypotheses

2.1. Cross-Industry Technology Spillover Perception (CTSP) and Cross-Industry Innovation Performance. Cross-industry technology spillover perception (CTSP) refers to the degree to which the enterprise absorbs the technology spilling from outside industries [5]. It is the ability of enterprises to absorb and feedback the technologies of outside industries, which could affect the cross-industry innovation performance. Consistent with the generally accepted practice in technology spillover studies [17, 18], we divided CTSP into cross-industry technology spillover perception width (CTSP-Width) and cross-industry technology spillover perception depth (CTSP-Depth). The following analysis is carried out on the basis of this division.

2.1.1. CTSP-Width and Cross-Industry Innovation Performance. CTSP-Width refers to the scope of outside industries from which the enterprise absorbs the knowledge when conducting the cross-industry innovation. The enterprise with wide CTSP-Width has a greater opportunity to obtain heterogeneous technological solutions [2, 15], which can provide the required knowledge base for cross-industry innovation [18]. Existing studies demonstrated that enterprises enable analogical thinking to deploy heterogeneous knowledge and conduct cross-industry innovation [2, 19]. If appropriately applied, it can contribute significantly to the performance of cross-industry innovation [19]. On the other hand, the wider CTSP-Width helps to reduce the search cost of cross-industry technology [20, 21]. A wide range of outside technology and knowledge perceived and absorbed by the enterprise could help to shorn the trial and error process of innovation resource search [22]. It can significantly reduce the time invested in R&D, improve R&D efficiency, and accelerate the speed of innovation [23], which further promotes the cross-industry innovation performance.

However, the impact of CTSP-Width on cross-industry innovation performance may change. In the early stage of industry development, enterprises’ R&D inertia is relatively low [24], and their adaptability to heterogeneous technologies is high [25]. But, along with the industry’s continuous development, cognitive inertia may become rooted in the technological paradigm. Once a strong path dependence is formed, the facilitation effect of CTSP-Width on cross-industry innovation performance may weaken or even disappear [26, 27]. Especially when the enterprise has a clear target industry to enter, at this time, the one that has an impact on innovation performance is more likely to be the in-depth mastery of the technical knowledge of the target industry rather than just to have a tiny sip of a wide range of outside technological knowledge. Accordingly, we hypothesize the following:

Hypothesis 1. In different periods of industry development, CTSP-Width positively impacts on the enterprises’ cross-industry innovation performance. However, the positive impacts would gradually become weakened or insignificant along with the industry development.

2.1.2. CTSP-Depth and Cross-Industry Innovation Performance. CTSP-Depth reflects the enterprise’s absorption intensity of knowledge from outside industries in cross-industry innovation activities. It is generally measured by the number or frequency that the enterprise makes use of the technical knowledge of outside industries. A high level of CTSP-Depth may promote the enterprise’s capability of cross-industry innovation and further improve the cross-industry innovation performance. Firstly, when deeply perceiving and absorbing the technical knowledge of one or several outside industries, the enterprise may no longer simply copy but can realize creative imitation [2] and create new technology or knowledge [28]. Secondly, when deeply perceiving the cross-industry technology spillover, in particular, when appearing cross-industry cooperation behaviors, the enterprise is not only able to learn the explicit technical knowledge from outside industries but also able to explore and learn the tacit knowledge [29, 30]. Thirdly, the enterprise’s deep perception of technology spillover from outside industries indicates the enterprise’s frequent knowledge interaction with one or several outside industries. It would
establish a sense of familiarity and trust, which may reduce the difficulty of knowledge searching, distinguishing, and screening [18] and form stable, reliable, and efficient technical knowledge acquisition channels [31], providing a good resource base for cross-industry innovation.

As mentioned above, when the industry is relatively mature, the enterprise has a clear goal for cross-industry innovation and a determined target industry to enter. At this time, its deep technology perception and utilization are more likely to be transformed into innovation output. The deep perception of cross-industry technology spillover will help enterprises to determine which is the valuable innovation resource, then improve the effectiveness of R&D investment in targeted cross-industry innovation [16], and finally improve the cross-industry innovation performance. Accordingly, we hypothesize the following:

Hypothesis 2. In different periods of industry development, CTSP-Depth positively impacts on the enterprises’ cross-industry innovation performance. The positive impacts would gradually become enhanced along with the industry development.

2.2. Knowledge Flow in Knowledge Network and Cross-Industry Innovation Performance. The cross-industry knowledge network is formed through cross-industry patent citation among enterprises. In the cross-industry knowledge network, node enterprises interact with each other through cross-industry technology spillover, which is discussed in Hypotheses 1 and 2. Meanwhile, the intraindustry citation of patents also forms the intraindustry knowledge network. The structural characteristics and knowledge flow of enterprises in the intraindustry knowledge network can affect intraindustry technology and knowledge diffusion [32, 33], as well as innovation performance. Therefore, we further explore the role of intraindustry knowledge networks on cross-industry innovation performance.

The knowledge network mentioned in this paper refers to the intraindustry knowledge network. Based on existing studies, we divided the measurement of enterprises’ knowledge flow in the knowledge network into knowledge contribution and knowledge profitability [1].

2.2.1. Knowledge Contribution and Cross-Industry Innovation Performance. Knowledge contribution refers to the benefits the enterprise brings to other network member enterprises when it diffuses and overflows its knowledge to the knowledge network [1]. In general, the enterprise with the higher knowledge contribution acts as the incumbent in the innovation network and obtains more knowledge power and resources, which facilitates the enterprise’s incremental innovation [34, 35]. By the contrary, the higher knowledge contribution may not be conducive to cross-industry innovation. On the one hand, the higher knowledge contribution implies that the enterprise has stronger network embeddedness [36]. The network embeddedness may solidify the enterprise’s innovation thinking and behavior in the existing innovation network, which is not conducive to cross-industry innovation [24, 37, 38]. On the other hand, if the enterprise’s knowledge contribution is high, it reflects that the enterprise has strong R&D capability of technology and knowledge in the internal industry. In this case, if the enterprise allocates its R&D resources to cross-industry technology R&D, which it is not very good at, it will generate opportunity cost and low innovation efficiency [35, 39]. Therefore, such enterprises are usually more willing to invest resources in the technology of their own industry, resulting in “crowding-out effect” [35] on cross-industry innovation.

When the industry is relatively mature, the degree of network embeddedness and technology R&D inertia is stronger [24], and the impact of knowledge contribution may be more obvious. When an enterprise makes a high contribution to the knowledge network in its own industry, even if it perceives the technology spillover from outside industries, it may not have enough motivation and force to conduct cross-industry innovation due to the network iner-tia and investment “crowding out effect” as mentioned above. In contrast, if an enterprise does not occupy a high centrality in the knowledge network in its industry, its freedom of entry and exit would be relatively high. Such enterprises are more likely to transform the perceived cross-industry technology spillover into cross-industry innovation. Accordingly, we hypothesize the following:

Hypothesis 3. In different periods of industry development, the impacts of CTSP-Width on cross-industry innovation performance are negatively moderated by enterprises’ knowledge contribution to the knowledge network.

Hypothesis 4. In different periods of industry development, the impacts of CTSP-Depth on cross-industry innovation performance are negatively moderated by enterprises’ knowledge contribution to the knowledge network.

2.2.2. Knowledge Profitability and Cross-Industry Innovation Performance. Enterprises’ knowledge base for cross-industry innovation comes not only from the technology spillover of outside industries but also from the knowledge absorption from the intraindustry knowledge network, i.e., the level of enterprise’s knowledge profitability [1]. The effect of knowledge profitability is mainly determined by the heterogeneity of the knowledge that the enterprise absorbed and the enterprise’s knowledge search scope and cognitive scope. Firstly, the knowledge absorbed from intraindustry knowledge network is usually homogeneous. Consequently, it contributes less to the heterogeneous knowledge base that is required for cross-industry innovation [14]. Secondly, the enterprise frequently absorbing knowledge from the intraindustry knowledge network makes it easy to generate path dependence, which is not conducive to expanding the scope of knowledge searching [11, 40]. Thirdly, the enterprise absorbing knowledge from the intraindustry knowledge network makes it easy to generate cognitive inertia, which is not conducive to find cross-industry technology solutions [2, 41].

Enterprise’s knowledge profitability plays an important role in determining the knowledge accumulation related to cross-industry innovation, because it can determine which knowledge is used for innovation [21], and thus determine
what kind of innovation will be brought, e.g. incremental, radical, or cross-industry innovation. This implies that the enterprise’s knowledge profitability and CTSP may have a joint effect on cross-industry innovation performance. In the case of high knowledge profitability, the enterprise spends a lot of effort to absorb and utilize the intraindustry knowledge. In this case, even if with a high CTSP, the enterprise may still not be able to effectively transform it into cross-industry innovation. Comparatively, in the case of low knowledge profitability, the enterprise has the capacity to digest and integrate outside industry knowledge [21], which may bring a better cross-industry innovation performance. Accordingly, we hypothesize the following:

**Hypothesis 5.** In different periods of industry development, the impacts of CTSP-Width on cross-industry innovation performance are negatively moderated by enterprises’ knowledge profitability in the knowledge network.

**Hypothesis 6.** In different periods of industry development, the impacts of CTSP-Depth on cross-industry innovation performance are negatively moderated by enterprises’ knowledge profitability in the knowledge network.

### 3. Methodology

#### 3.1. The Data

The research setting of this study is the unmanned aerial vehicle industry (UAV). The UAV industry has obvious characteristics of cross-industry technology spillover [6, 42]. UAV was first used in the military fields as an aerospace technology and then gradually extended to civilian fields such as rescue, monitoring, transportation, agriculture, and forestry [5]. In recent years, it has become the carrier of technologies such as sensor, AI, CV, and AR/VR, spilling over many industries. Meanwhile, UAV is the representative of high-tech industry. It developed rapidly in recent years and may have further extensive influence in the next few years [43]. It is of great significance to explore the cross-industry technology spillover and cross-industry innovation of UAV industry.

We collected patents from Derwent Innovation Index database to empirically test our hypotheses. We followed Wu et al. [5] by setting the query condition “TS=(( unmanned OR automatic OR autonomous) AND (aircraft OR "aerial vehicle*" OR airship* OR drone)) OR "UAV*" )” to filter for UAV patents. Considering the development process of UAV industry, we retained the patents applied from 2016-01-01 to 2020-12-31. Due to the considerable patent base and large number of patentees in UAV industry, according to the distribution characteristics of patentees (the number of patent holders whose patent holding proportion is less than 0.2% has a significant decline and scattered distribution), we retained 80 enterprises whose patent applications account for more than 0.2% of the total patents in 2006 to 2020. Totally 67,764 patents were collected on July 8, 2021. The specific information of each patentee is shown in Table 1.

#### 3.2. Data Processing

The technology upgrading and updating speed of UAV industry is so fast that the patents quickly lose their technical value in about 5 years [44]. Therefore, we took the patentee’s patent data in the 5-year time window as the research sample. Figure 1 shows the trend of patent applications in UAV industry from 2006 to 2020. Taking five years as the time window, it is divided into three stages: the first is the flat period from 2006 to 2010, the second is the low-speed climbing period from 2011 to 2015, and the third is the high-speed growing period from 2016 to 2020. Based on the division of UAV industry development periods, we analyzed the impacts of cross-industry technology spillover perception and knowledge network on cross-industry innovation performance in different periods.

We processed the patent data of 80 patentees as the following process: firstly, we extracted the patent citation information among patentees and constructed the 80 * 80 patentee citation matrix (PP matrix). Each value in the PP matrix represents the number of the patents owned by the enterprise of the corresponding column that is cited by the enterprise of the corresponding row. Secondly, we extracted the International Patent Classification (IPC) number of the patentees’ forward citing patents, i.e., the patents cited by the patentees. Taking the concordance table between the International Patent Classification (IPC) and the International Standard Industrial Classification (ISIC-rev. 2) as the base for dividing industries [45], we classified the patentees’ forward citation patents into 25 industrial classifications according to their IPCs and constructed the patentees’ forward citing patent-industry matrix (CI matrix). For example, one patent cited by one of the patentees contains two IPCs, G05B and G05D. According to the IPC-ISIC concordance table, both IPCs correspond to Class 13. Therefore, the value in the corresponding industry row of the patentee in the CI matrix is added by 2. Thirdly, we extracted the IPCs of the patentees’ newly applied patents. In the same measure, we classified the patentee’s newly applied patents into 25 industrial classifications according to their IPCs based on the IPC-ISIC concordance table [45] and constructed the patentee’s newly applied patent-industry matrix (AI matrix). For example, one newly applied patent of the patentee contains three IPCs, i.e., H03B, C21B, and A61N. According to the IPC-ISIC concordance table, they correspond to Class 2, Class 10, and Class 13, respectively. The values in the corresponding three industry rows of the patentee in the AI matrix are added by 1. Based on these matrices, we calculated the measurements of the variables; the details are shown in the next subsection. Finally, with SPSS 23.0, we carried out the descriptive statistical analysis, correlation analysis, and hierarchical regression analysis to test the hypotheses.

#### 3.3. Variables

##### 3.3.1. CTSP-Width and CTSP-Depth

Drawing on the definition and measurement method of industry perception coefficient in the study of cross-industry technology spillover by Wu et al. [5], CTSP-Width is measured by the number of outside industrial classifications cited by the patentees,
and CTSP-Depth is measured by the number of patents’ IPCs belonging to outside industrial classifications cited by the patentees. To avoid the deviation caused by the patentee’s basic technical ability, we weighted the above two measurements by dividing the total patent number.

\[
\text{CTSP-Width}_i = \frac{\sum_{j=1}^{m-1} \text{InCiting}_\text{industry}^j}{\text{Total}_i}, \\
\text{CTSP-Depth}_i = \frac{\sum_{j=1}^{m-1} \text{InCiting}_\text{patent}^j}{\text{Total}_i},
\]

Table 1: Patent information of 80 patentees.

| Rank | Patentee | Number of patents | Proportion (%) | Rank | Patentee | Number of patents | Proportion (%) |
|------|----------|-------------------|----------------|------|----------|------------------|----------------|
| 1    | Shen-n   | 3054              | 4.507          | 41   | Chan-n   | 273              | 0.403          |
| 2    | Dji-c    | 1891              | 2.791          | 42   | Hebe-n   | 272              | 0.401          |
| 3    | Guan-n   | 1658              | 2.447          | 43   | Szai-c   | 271              | 0.4            |
| 4    | Beij-n   | 1649              | 2.434          | 44   | Hube-n   | 270              | 0.398          |
| 5    | Shan-n   | 1385              | 2.044          | 45   | Cetc-c   | 260              | 0.384          |
| 6    | Boei-c   | 1125              | 1.66           | 46   | Wuxi-n   | 249              | 0.376          |
| 7    | Jian-n   | 1125              | 1.66           | 47   | Dong-n   | 236              | 0.348          |
| 8    | Sgcc-c   | 1020              | 1.505          | 48   | Fosh-n   | 217              | 0.32           |
| 9    | Chen-n   | 943               | 1.392          | 49   | Zhen-n   | 217              | 0.32           |
| 10   | Nanj-n   | 920               | 1.358          | 50   | Qdgr-c   | 214              | 0.316          |
| 11   | Chav-c   | 824               | 1.216          | 51   | Hymr-c   | 213              | 0.314          |
| 12   | Xian-n   | 775               | 1.144          | 52   | Ibm-c    | 213              | 0.314          |
| 13   | Tian-n   | 736               | 1.086          | 53   | Liao-n   | 211              | 0.311          |
| 14   | Cspg-c   | 674               | 0.995          | 54   | Smsc-c   | 206              | 0.304          |
| 15   | Eads-c   | 579               | 0.854          | 55   | Text-c   | 202              | 0.298          |
| 16   | Sich-n   | 578               | 0.853          | 56   | Rayt-c   | 200              | 0.295          |
| 17   | Hena-n   | 560               | 0.826          | 57   | Zhon-n   | 199              | 0.294          |
| 18   | Zhej-n   | 512               | 0.756          | 58   | Zhou-i   | 190              | 0.28           |
| 19   | Zhan-i   | 491               | 0.725          | 59   | Hefe-n   | 189              | 0.277          |
| 20   | Unba-c   | 485               | 0.716          | 60   | Xiam-n   | 188              | 0.277          |
| 21   | Suzh-n   | 476               | 0.702          | 61   | Prod-n   | 180              | 0.266          |
| 22   | Anhu-n   | 475               | 0.701          | 62   | Roro-c   | 176              | 0.26           |
| 23   | Wang-i   | 443               | 0.654          | 63   | Uyzh-c   | 174              | 0.257          |
| 24   | Qing-n   | 441               | 0.651          | 64   | Lock-c   | 168              | 0.248          |
| 25   | Unwp-c   | 431               | 0.636          | 65   | Ning-n   | 166              | 0.245          |
| 26   | Caer-c   | 411               | 0.607          | 66   | Qcom-c   | 164              | 0.242          |
| 27   | Unua-c   | 403               | 0.595          | 67   | Wama-c   | 155              | 0.229          |
| 28   | Amaz-c   | 397               | 0.586          | 68   | Gene-c   | 154              | 0.227          |
| 29   | Hang-n   | 391               | 0.577          | 69   | Shaa-n   | 154              | 0.227          |
| 30   | Hone-c   | 385               | 0.568          | 70   | Undt-c   | 154              | 0.227          |
| 31   | Gzxt-c   | 360               | 0.531          | 71   | Beit-c   | 153              | 0.226          |
| 32   | Wuha-n   | 351               | 0.518          | 72   | Itlc-c   | 153              | 0.226          |
| 33   | Chon-n   | 346               | 0.511          | 73   | Thls-c   | 148              | 0.218          |
| 34   | Huna-n   | 339               | 0.5            | 74   | Brax-c   | 146              | 0.215          |
| 35   | Chen-i   | 334               | 0.493          | 75   | Aero-n   | 145              | 0.214          |
| 36   | Aute-n   | 330               | 0.487          | 76   | Sony-c   | 141              | 0.208          |
| 37   | Ewat-c   | 327               | 0.483          | 77   | Uscg-c   | 140              | 0.207          |
| 38   | Wuhu-n   | 311               | 0.459          | 78   | Huan-i   | 139              | 0.205          |
| 39   | Zhuh-n   | 301               | 0.444          | 79   | Yunn-n   | 137              | 0.202          |
| 40   | Yang-i   | 283               | 0.418          | 80   | Glds-c   | 136              | 0.201          |
calculated by the number of nonzero values in column $i$ of CI matrix, except for Class 8 which is the original industrial classification UAV is in. The nonzero value in column $i$ indicates that enterprise $i$ cited some patents and their IPCs belong to the corresponding industrial classifications. For example, enterprise $i$ cited the patents whose IPCs belonging to three industrial classifications except Class 8. Thus, there will be three nonzero values in column $i$ of CI matrix and $\sum_{j=1}^{m-1} \text{InCiting}_j \text{industry} = 3$ correspondingly. $\sum_{j=1}^{m-1} \text{InCiting}_j \text{ppatent}$ is calculated by the sum of values in column $i$ of CI matrix, also except for Class 8. For example, enterprise $i$ cited several patents with a total of twenty-one IPCs, including seven belonging to Class 1, three belonging to Class 2, five belonging to Class 8, and six belonging to Class 24. Thus, each corresponding value in column $i$ of CI matrix is 7, 3, 5, and 6. And $\sum_{j=1}^{m-1} \text{InCiting}_j \text{ppatent}$ equals to 16 ($21 - 5 = 16$).

3.3.2. Knowledge Contribution (KC) and Knowledge Profitability (KP). According to the definition and measurement method of knowledge flow in knowledge network by Cao and Sun [1], the knowledge flow of enterprises mainly includes four aspects: internal absorption, external absorption, inward diffusion, and outward diffusion. Enterprises spread their knowledge outward and generate spillover value to other network nodes, which is reflected by knowledge contribution (KC). Enterprises absorb knowledge from outside and gain potential growth value to themselves, which is reflected by knowledge profitability (KP). The calculation formula is

$$\text{KC}_i = \frac{\sum_{j=1}^{n} k_{ij} - k_{ii}}{\text{Total}_i},$$

$$\text{KP}_i = \frac{\sum_{j=1}^{n} k_{ji} - k_{ii}}{\text{Total}_i},$$

where $\text{KC}_i$ and $\text{KP}_i$ are the knowledge contribution level and knowledge profitability level of enterprise $i$, respectively. Total$_i$ is the total number of patents owned by enterprise $i$, $n$ is the total number of enterprises, and $k_{ij}$ is the number of enterprise $i$’s patents that cited by enterprise $j$, i.e., the value of row $j$ in column $i$ in PP matrix. For example, if 1000 patents of enterprise $i$ were cited, including 10 cited by itself and 990 cited by other enterprises, then $\sum_{j=1}^{n} k_{ij} - k_{ii}$ equals to 990. In addition, if enterprise $i$ totally cited 100 patents, including 10 of its own and 90 of other enterprises, then $\sum_{j=1}^{n} k_{ji} - k_{ii}$ equals to 90. The enterprises whose KC and KP are high have more two-way knowledge interaction with other members, indicating a more important role in the knowledge network.

3.3.3. Cross-Industry Innovation Performance (CIP). Drawing on the method for measuring innovation performance by Li and Yu [46], we measured cross-industry innovation performance (CIP) by calculating the proportion of cross-industry IPCs included in the new patents applied by enterprises in different time windows. The standard for measuring cross-industry IPCs is also according to the IPC-ISIC concordance table. All IPCs in addition to the ones classified as Class 8 are regarded as cross-industry IPCs. The calculation formula for CIP is

$$\text{CIP}_i = \frac{\sum_{j=1}^{m} \text{pij} - \text{pi}_{\text{ai}}}{\sum_{j=1}^{m} \text{pij}},$$

where CIP$_i$ is enterprise $i$’s cross-industry innovation performance, $m$ is the total number of industrial classifications ($m = 25$), and pij is the number of IPCs included in the patents applied by enterprise $i$ belonging to industrial classification $j$, i.e., the value of row $j$ in column $i$ in AI matrix. For example, if enterprise $i$ applied several patents with totally 100 IPCs, including 5 belonging to Class 8 which is the original industrial classification of UAV and 95 belonging to other industrial classifications, then $\sum_{j=1}^{m} \text{pij}$ equals to 100, and $\sum_{j=1}^{m} \text{pij} - \text{pi}_{\text{ai}}$ equals to 95.

3.3.4. Control Variables. Existing studies have reached an agreement that enterprises with different properties have great differences in their need for innovation resources.
Therefore, we introduced the enterprise property (EP) into the model as the control variable. According to the classification of enterprise property in Derwent Innovation Index database, the patentees are divided into three types: standard enterprises are assigned 0, nonstandard enterprises are assigned 1, and private enterprises are assigned 2. Meanwhile, the technical level of enterprises may have an impact on the cross-industry innovation performance. Thus, we also introduced the enterprises’ technical level (TL) into the model as the other control variable. TL is measured by the number of patents applied by enterprises in different time windows.

To avoid the influence of variable magnitude difference on the readability of the results, we standardized the independent variables (CTSP-Width, CTSP-Depth), moderator variables (KC, KP), and control variables (TL). The calculation formula is

\[ x' = \frac{x - \min (x)}{\max (x) - \min (x)} \]

where \( x' \) is the standardized value, \( x \) is the original value, \( \max (x) \) is the maximum value in \( x \), and \( \min (x) \) is the minimum value in \( x \).

**4. Empirical Results**

**4.1. Correlation Analysis.** The phased output results of variables’ mean, standard deviation, and correlation coefficients are shown in Table 2. To further test the possible multicollinearity between independent variables, we conducted the variance inflation factor test (VIF test). The results of VIF test show that the tolerance of all variables is greater than 0.2 and the VIF is less than 10. Therefore, it can be judged that there is no multicollinearity between variables.

4.2. Regression Analysis. We conducted the hierarchical regression test on different periods of UAV industry development. The hierarchical regression process and result outputs are shown in Table 3.

In the flat period, the results of model 1~model 6 show that CTSP-Width has a significant positive impact on cross-industry innovation performance (\( \beta = 0.240, p < \)}
Table 3: Regression results.

| Dependent variable | Stages               | Model | EP  | TL  | CTSP-Width | CTSP-Depth | KC  | KP  | CTSP-Width * KC | CTSP-Depth * KC | CTSP-Width * KP | CTSP-Depth * KP | $R^2$ | Adjusted $R^2$ | $\Delta R^2$ |
|--------------------|----------------------|-------|-----|-----|------------|------------|-----|-----|----------------|----------------|----------------|----------------|-------|----------------|-----------|
|                    | Flat period          | Model 1 | 0.001 | -0.155 |            |            |     |     |                |                |                |                | 0.087 | 0.041 | —             |
|                    |                      | Model 2 | -0.027 | -0.093 | 0.240*** | 0.063 |     |     |                |                |                |                | 0.468 | 0.412 | 0.381         |
|                    |                      | Model 3 | -0.027 | -0.093 | 0.240**  | 0.063     | 0.009 | -0.003 |                |                |                |                | 0.468 | 0.379 | 0.000         |
|                    |                      | Model 4 | -0.024 | -0.087 | 0.238**  | 0.044     | -0.012 |        | 0.284          |                |                |                | 0.471 | 0.383 | 0.003         |
|                    |                      | Model 5 | -0.030 | -0.083 | 0.273**  | 0.090     | -0.025 | -0.079 |                |                |                |                | 0.482 | 0.395 | 0.011         |
|                    |                      | Model 6 | -0.029 | -0.064 | 0.253*** | 0.108     | -0.037 |        | -0.070          | 0.480          | 0.393          | -0.002         |       |                |           |
|                    |                      | Model 7 | -0.120** | -0.011 |            |            |     |     |                |                |                |                | 0.101 | 0.076 | —             |
|                    |                      | Model 8 | -0.076 | -0.003 | 0.231     | 0.303**   |     |     |                |                |                |                | 0.241 | 0.197 | 0.140         |
|                    |                      | Model 9 | -0.065 | -0.005 | 0.093     | 0.304*    | 0.669 | -0.441 |                |                |                |                | 0.257 | 0.192 | 0.016         |
|                    |                      | Model 10 | -0.066 | -0.083 | 0.014     | 0.452**   | 0.960 |        | -2.048          |                |                |                | 0.270 | 0.206 | 0.013         |
|                    |                      | Model 11 | -0.055 | -0.069 | 0.445*    | 0.315*    | 0.295 |        | -1.222*         | 0.286          | 0.223          | 0.016         |       |                |           |
|                    |                      | Model 12 | -0.054 | -0.095 | 0.182     | 0.912***  | 0.608** |        | -1.766***       | 0.383          | 0.329          | 0.097         |       |                |           |
|                    |                      | Model 13 | -0.131*** | -0.005 |            |            |     |     |                |                |                |                | 0.379 | 0.362 | —             |
|                    |                      | Model 14 | -0.087*** | 0.056  | 0.037     | 0.274**   |     |     |                |                |                |                | 0.492 | 0.465 | 0.113         |
|                    |                      | Model 15 | -0.088*** | 0.087  | 0.078     | 0.210*    | 0.214*  | -0.185 |                |                |                |                | 0.531 | 0.493 | 0.039         |
|                    |                      | Model 16 | -0.077*** | 0.052  | -0.076    | 0.553***  | 0.337*** |        | -0.648**       |                |                |                | 0.584 | 0.550 | 0.053         |
|                    |                      | Model 17 | -0.089*** | 0.068  | 0.134     | 0.298**   | -0.010 |        | -0.336          | 0.500          | 0.459          | -0.084        |       |                |           |
|                    |                      | Model 18 | -0.064**  | 0.065  | 0.006     | 0.754***  | 0.306*  |        | -1.578**        | 0.551          | 0.514          | 0.051         |       |                |           |

***, **, and * suggest that the parameter estimates are significant at 0.1%, 1%, and 5%, respectively.
0.001). But the impact of CTSP-Depth on cross-industry innovation performance is not significant ($\beta = 0.063, \text{ns}$). On the basis of the main effect model, the moderating effects of CTSP-Width and KC, CTSP-Width and KP, CTSP-Depth and KC, and CTSP-Depth and KP are introduced, respectively. The results show that neither knowledge contribution nor knowledge profitability shows a significant moderating effect ($\beta = -0.003, \text{ns}; \beta = 0.284, \text{ns}; \beta = -0.079, \text{ns}; \beta = -0.070, \text{ns}$).

In the low-speed climbing period, the results of model 7–model 12 show that the impact of CTSP-Width on cross-industry innovation performance is not significant ($\beta = 0.231, \text{ns}$). CTSP-Depth has a significant positive impact on cross-industry innovation performance ($\beta = 0.303, p < 0.01$). On the basis of the main effect model, the moderating effects of CTSP-Width and KC and CTSP-Depth and KC are introduced, respectively. The results show that knowledge contribution does not show a significant moderating effect ($\beta = -0.441, \text{ns}; \beta = -2.048, \text{ns}$). On the basis of the main effect model, the moderating effects of CTSP-Width and KP and CTSP-Depth and KP are introduced, respectively. The results show that knowledge profitability negatively moderates the impact of CTSP on cross-industry innovation performance ($\beta = -1.222, p < 0.05; \beta = -1.766, p < 0.001$).

In the high-speed growing period, the results of model 13–model 18 show that the impact of CTSP-Width on cross-industry innovation performance is not significant ($\beta = 0.037, \text{ns}$). CTSP-Depth has a significant positive impact on cross-industry innovation performance ($\beta = 0.274, p < 0.01$). On the basis of the main effect model, the moderating effects of CTSP-Width and KC and CTSP-Depth and KC are introduced, respectively. The results show that knowledge contribution does not significantly moderate the impact of CTSP-Width on cross-industry innovation performance; however, it negatively moderates the impact of CTSP-Depth on cross-industry innovation performance ($\beta = -0.185, \text{ns}; \beta = -0.648, p < 0.01$). On the basis of the main effect model, the moderating effects of CTSP-Width and KP and CTSP-Depth and KP are introduced, respectively. The results show that knowledge profitability does not significantly moderate the impact of CTSP-Width on cross-industry innovation performance; however, it negatively moderates the impact of CTSP-Depth on cross-industry innovation performance ($\beta = -0.336, \text{ns}; \beta = -1.578, p < 0.01$).

According to the results of hierarchical regression analysis in Table 3, we draw the influence mechanism diagram between CTSP, knowledge flow, and cross-industry innovation performance, as shown in Figure 2.

We further visualized the moderating effects of knowledge flow on the relationships between CTSP and cross-industry innovation performance, as shown in Figure 3. Only significant moderating effects are shown, while insignificant ones are not. Figure 3(a) shows that in the low-speed climbing period, when the level of knowledge profitability is high, the positive impact of CTSP-Depth on cross-industry innovation performance will weaken. Figures 3(b) and 3(c) show that in the high-speed growing period, when the level of knowledge contribution is higher, the positive impact of CTSP-Depth on cross-industry innovation performance will weaken; when the level of knowledge profitability is high, the positive impact of CTSP-Depth on cross-industry innovation performance will also weaken. Moreover, the negative moderating effect of knowledge profitability is stronger than that of knowledge contribution.

5. Discussions

5.1. Theoretical Implications. Our first key finding is that the impacts of CTSP and knowledge flow on cross-industry innovation performance change dynamically along with the evolution of industry. Specifically, in the flat period of industry development, only CTSP-Width has a direct impact on cross-industry innovation performance. When the industry gradually goes into the low-speed climbing period and the high-speed growing period, the one that has the direct impact of cross-industry innovation performance becomes CTSP-Depth, instead of CTSP-Width, and the moderating effects of knowledge flow gradually appear. These dynamic changes are the result of the comprehensive effect of various internal and external changes along with industry development, including the changes in the capability of enterprises to identify and utilize cross-industry technologies, the changes in the degree of homogenization and heterogeneity of knowledge faced by enterprises, and the changes in the scale and structure of innovative knowledge networks, etc. This finding extends existing studies on cross-industry innovation [15, 48] with a new perspective and content, i.e., revealing the influencing mechanism among CTSP, knowledge...
flow, and cross-industry innovation performance from the perspective of dynamic process.

Our second key finding is that by distinguishing the width and depth of CTSP, we found the evolution of their impacts on cross-industry innovation performance in different periods. This finding is to some extent consistent with the study of Zhang et al. [15] on the relationship between technology accumulation and cross-industry innovation performance, but extends Zhang’s study by investigating more specific variables. In the flat period, CTSP-Width positively impacts cross-industry innovation performance. And then, the positive effect of CTSP-Width turns to insignificant at the low-speed climbing and high-speed growing period. The positive impact of CTSP-Depth will not appear until the low-speed climbing period and remains significant in the latter two periods. This finding may extend our understanding about how the heterogeneous CTSP impacts on cross-industry innovation performance. In the flat period, the high CTSP-Width implies that the enterprise has the technology boundary spanning advantage of the diversified outside industrial technology and knowledge [49, 50]. When the industry development direction is not clear and the dominant design has not been determined, the technology boundary spanning advantage will facilitate the generation of creative ideas for cross-industry innovation [51], as well as facilitate the application of analogical thinking to enterprise’s own industry [52], and then improve the cross-industry innovation performance. When the industry grows to maturity, the development direction is gradually clear, and the dominant design is gradually emerging. The whole industry has a specific target for entry. At this time, the positive effect of CTSP-Width may be no longer significant, or even turn to negative. Accordingly, the deep perception of technology spillover from the target-entry industry would be more conductive to cross-industry innovation performance.

Our third key finding is that we found the knowledge network trap in cross-industry innovation. By constructing the knowledge network through the patent citation data in UAV industry, we found that, from the low-speed climbing period, knowledge profitability begins to negatively moderate the positive impact of CTSP-Depth on cross-industry innovation performance, and the moderating effect will continue in the subsequent period. From the high-speed growing period, knowledge contribution begins to negatively moderate the positive impact of CTSP-Depth on cross-industry innovation performance. However, the moderating effect of knowledge contribution is weaker than that of knowledge profitability. This finding advances existing studies on knowledge network evolution in cross-industry innovation [1] by further uncovering the joint effects of CTSP and knowledge network on cross-industry innovation performance. The high level of knowledge profitability may inhibit the positive impact of CTSP-Depth on cross-industry innovation performance by creating the path dependence on intraindustry knowledge network. Moreover, the high level of knowledge contribution may also inhibit the relationship by creating knowledge power and network embeddedness. The path dependence, knowledge power, or network embeddedness are the products of the expansion of industry innovation networks. When the industry is relatively mature, the related network effects arise, and then, the
contribution and profitability of enterprises in the knowledge network will negatively moderate the impacts of CTSP on cross-industry innovation performance, which becomes a trap of cross-industry innovation and makes enterprises fall into an innovation dilemma.

5.2. Practical Implications. Driven by both external industrial transformation and internal development demand, enterprises are urgent for cross-industry innovation to lay out and realize the cross-industry development strategies. Meanwhile, cross-industry innovation is also an effective way for enterprises to break through the bottleneck of development and innovation [2]. Our empirical results can provide the following two references for enterprises in technology intensive industries, e.g., UAV, and their cross-industry innovation practice.

First, enterprises should improve their sensitivity to the development level of their own industry. They should dynamically adjust their searching and absorbing strategies for technology and knowledge of outside industries, depending on the different industrial development periods they are in. Specifically, in the flat development period, enterprises need to widely search and absorb the technology and knowledge of outside industries to avoid an untimely solidifying direction of cross-industry innovation. In the low-speed climbing and high-speed growing period, the cross-industry dominant design appears. At this time, enterprises need to shift their focus to one or several target industries under the dominant design and concentrate on creatively absorbing their technology and knowledge, to promote the efficiency and output of cross-industry innovation.

Second, enterprises should strive to overcome the cognitive inertia brought by their internal industry knowledge network and avoid falling into the trap of knowledge network. In particular, when the industry grows to mature and the network embeddedness increases, the enterprise needs to keep itself sober. On the one hand, enterprises should rationally treat the knowledge power brought by the high knowledge contribution. They should be aware that higher knowledge power can attract more R&D human resources, capital, and other innovation resources; however, it will weaken the positive impact of CTSP on cross-industry innovation performance. On the other one hand, enterprises need to reasonably control their absorption of technology and knowledge from the intraindustry knowledge network, to avoid falling into “over dependence” and technology path solidification and minimize the adverse influence on cross-industry innovation.

6. Conclusions

To reveal how the enterprise’s CTSP impacts its cross-industry innovation performance, we divided the degree of CTSP into CTSP-Width and CTSP-Depth and introduced the enterprise’s knowledge flow in knowledge network into the research framework. The empirical results based on the patent data in UAV industry show that CTSP-Width positively impacts on cross-industry innovation performance in the early stage of UAV industry, and then, this impact gradually fades away while the positive impact of CTSP-Depth becomes significant. Meanwhile, we also found that along with the development of UAV industry, the knowledge network of UAV industry would gradually become a trap that negatively moderates the impacts mentioned above.

There are some limitations in this study, which deserve further investigation in the future. First, we investigated only the UAV industry, and it may need to further verify whether the conclusions are also suitable for explaining the cross-industry innovation in other industries. Second, we measured the variables with only patent data. However, patent data may not be able to comprehensively reflect the variables, since not all enterprises will turn their achievements into patents in time. It may need to collect from multiple data sources to measure the variables from more perspectives and further verify the conclusions.

Although with the above limitations, this study still provides some insights and help for future research. First, the impact of some antecedents of cross-industry innovation, like CTSP in this study, may be dynamic. We enlighten future research to investigate cross-industry innovation from the perspective of dynamic process, which may help to reveal the mechanisms that cannot be found from a holistic perspective. Second, we call attention to a dialectical view on knowledge network. One of the focus in future research on knowledge network may be to discover the role of knowledge network in innovation under different circumstances, rather than trying to find universal conclusions.

Data Availability

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

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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