Team Knowledge-sharing in Virtual Teams: Evidence from Virtual R&D Teams in South Korea

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In recent years, the volume of remote R&D projects has increased substantially in South Korea as organizations seek to adapt to globalization and digital collaboration. While virtual teams are often considered catalysts for innovation, empirical evidence on how their structural and relational characteristics influence knowledge creation remains limited. The primary purpose of this study is to examine how organizational structures, social capital, and team capabilities jointly enhance the innovation performance of virtual R&D teams. Drawing on data from 73 virtual R&D teams in South Korea, we analyze innovation performance as measured by scientific papers and patents produced. The findings demonstrate that diverse team expertise significantly enhances paper publications, while adaptive learning exhibits a marginally positive effect on paper publication. Interestingly, prior ties demonstrate a negative association with paper publications, suggesting that over-embeddedness may impede creativity by restricting the introduction of fresh perspectives. These results underscore the importance of balancing capability development with the cultivation of novel linkages to maximize innovation outcomes. The study makes two key contributions: theoretically, it extends prior research by empirically identifying team-level drivers of performance within virtual R&D contexts; practically, it offers guidance for managers and policymakers in designing and supporting virtual R&D projects to foster innovation more effectively.

Keyword: adaptive learning, innovation performance, South Korea, social capital, team capability, virtual R&D teams

Ⅰ. Introduction

COVID-19, virtual R&D teams are now popular within organizations. Recently, growing numbers of teams have been working within a virtual environment and are geographically dispersed, forcing individuals to overcome space, time, and organizational boundaries (Ferraris et al., 2019; Gassmann and Von Zedtwitz, 2003). Virtual R&D teams are also characterized by a high degree of informal

Submission Date: 08. 24. 2025 Revised Date: (1st: 09. 11. 2025) Accepted Date: 09. 15. 2025
* The present research has been conducted by the partial support from the Research Grant of Kwangwoon University in 2024.

communication among team members due to the lack of formal rules, procedures, clear reporting relationships, and norms (Marlow et al., 2017; Monge and Contractor, 2001). The advancement of information and communication technologies (ICT) has made various types of virtual R&D teams feasible to efficiently coordinate R&D activities without needing to rely on face-to-face interactions (de Mattos et al., 2018). The international expansion of corporate R&D activities has urged many global companies to organize cross-border R&D projects in virtual settings (Ferraris et al., 2019). Also, the increasing application of the "open innovation" model driven by the accelerated convergence of technological innovations has bolstered the use of virtual R&D teams connecting universities, public R&D institutes, and private companies for collaborative R&D projects (Chesbrough, 2017; Chesbrough, 2003; Robin and Schubert, 2013). Well-designed virtual R&D teams fulfil the need to tap into local diversity, as well as support central creativity through the appropriate utilization of top-notch scientists and researchers (Gassmann and Von Zedtwitz, 2003; Ishikawa, 2024). However, because of the very nature of virtuality, such R&D teams are more vulnerable to mistrust, communication breakdowns, conflicts, and power struggles (Alom, 2025; Marlow et al., 2017; Rosen et al., 2007).

Despite the widespread use of virtual R&D teams and the notion that they can be useful for collaborative and innovative tasks, there is little empirical evidence of how team structure and characteristics impact knowledge creation (Ahuja and Carley, 1999; Hoch and Dulebohn, 2017; Wang et al., 2023). A highly unique study conducted by Ahuja et al. (2003), addressing the performance determinants of virtual R&D, examined the role of an individual's position in the process of knowledge creation. Also, recently, Natu and Aparicio (2022) discovered key factors influencing knowledge sharing, which included intrinsic motivation. Accordingly, their research provides only limited implications for practitioners desirous of organizing and managing virtual R&D teams effectively. To this end, understanding the design of the team structure is critical to effectively organizing the team (Furst et al., 1999; Park et al., 2024). In seeking to fill the gap in existing research, this study aims to empirically identify team-level variables affecting the performance of virtual R&D teams. This study makes two distinct contributions to the literature on virtual R&D teams. First, it extends Ahuja et al. (2003), who focused primarily on the role of individual network positions in shaping knowledge creation. While their micro-level analysis provided valuable insights into how individuals contribute to knowledge flows, it left unanswered how team-level structural and relational attributes influence overall team performance. Our study addresses this limitation by empirically examining team capability and social capital as collective-level drivers of knowledge sharing and innovation.

Second, this study empirically advances the integrative review by Dulebohn and Hoch (2017). Their synthesis highlighted antecedents such as trust, communication, and leadership as critical for virtual team success, but remained primarily conceptual in orientation, calling for more systematic empirical testing of team-level factors. Responding to that call, we provide robust evidence on how team design and embedded social capital jointly determine the performance of virtual R&D teams.

Together, these contributions position our research as a bridge between micro-level insights (Ahuja et al., 2003) and conceptual frameworks (Dulebohn and Hoch, 2017), offering a novel and empirically grounded framework for understanding how team structure and social capital jointly foster knowledge creation in virtual R&D contexts.

Whether virtual or not, R&D teams are designed to elicit synergies from complementary resources and team capabilities. Therefore, a pre-requisite for successful R&D teams is to endorse the team's diversity and the collective capabilities of individual members (Reagans and Zuckerman, 2001). In particular, a mechanism is needed to curb the downside of virtuality (i.e., being difficult to manage, costly to execute, never on time, and ineffective in achieving goals) (Gassmann and von Zedtwitz, 2003). Thus, we posit that, in addition to team capability, social capital embedded in virtual teams is critical in facilitating knowledge sharing and, hence, expediting the innovative performance of R&D projects.

Based on extant research, this study develops several hypotheses that identify the variables of team capability and social capital as antecedents of virtual R&D team performance. The proposed hypotheses are empirically tested using a sample of 73 Korean national R&D project teams funded by the Korean government to conduct frontier R&D in the areas of fundamental science and technology. This paper is organized as follows: In Section 2, we review the relevant literature and develop hypotheses. After that, in Section 3, we define variables and describe the data collection process. Data analysis and discussion of the result are subsequently explained in Section 4. Finally, we conclude with some academic and practical implications in Section 5.

Ⅱ. Literature review, theory and Hypotheses development

2.1 Team Capability and Social Capital in Virtual R&D Teams

The organizational characteristics of virtual

R&D teams are quite different from those of co-located R&D teams (Dulebohn and Hoch, 2017; Lee et al., 2010). Virtual R&D teams span more organizational boundaries than co-located ones, and their team structure tends to become decentralized. Team members usually have multiple responsibilities and possess different worldviews and, hence, have different communication and coordination mechanisms. Also, layered boundaries along space, time, and organizations create additional management complications.

Taking the characteristics of virtuality into consideration, an independent body of extant studies has sought to examine variables that explain virtual team performance. Kirkman et al. (2004) investigated the relationship between team empowerment and performance using 35 sales and service virtual teams in a high-technology organization. In this regard, they came up with the four dimensions of team empowerment—potency, meaningfulness, autonomy, and impact. Team empowerment was positively associated with such virtual team performance as process improvement and customer satisfaction. In addition, the number of face-to-face meetings moderates the relationship between team empowerment and process improvement. Ahuja et al. (2003) studied how individual role characteristics, such as function, status, and communication, affect individual performance in virtual teams. They accordingly found that individual role characteristics indirectly affect performance through a person's centrality in a team. However, despite profound interest in the subject, existing empirical studies have provided only patchy insight into this issue. There is, therefore, a significant need for research that expands the theoretical developments in the technology and innovation management field.

Extant research has identified team characteristics that affect performance in virtual R&D teams (Dulebohn and Hoch, 2017; Ha and Hong, 2020). The team characteristics frequently mentioned in the literature on virtual R&D teams include (i) good communication among members in virtual teams; (ii) a shared understanding of goals and objectives, task requirements, interdependencies, and roles and responsibilities; (iii) self-directed team control mechanisms; (iv) expertise of team members; and (v) the degree of virtuality (Ahuja et al., 2003; Gillespie et al., 2017; Hoch and Dulebohn, 2017; Kirkman et al., 2004). Given the hard-to-manage characteristics of virtual teams, it is unsurprising that research on virtual R&D teams has emphasized the management side of such teams, including communication, shared understanding, and control mechanisms, as key success factors (Bommel et al., 2021; Glikson and Erez, 2019; Marlow et al., 2017). Building on this research stream, we suggest that robust explanations for virtual R&D team performance can be derived via a marriage of the concepts of team capability and those of social capital, with a particular focus on social capital as an informal mechanism for knowledge-sharing and communication. Specifically, we argue that the innovative performance of a virtual R&D team is largely a function of both its collective individual capabilities and social capital. In this paper, innovative performance refers to the number of papers and patent publications produced by the virtual R&D team. Before turning to the social capital argument, we first build on our baseline hypothesis on team capability.

2.2 Team Capability and Innovation

The studies of organizational learning assert that tacit knowledge is derived from the learning-by-doing process and is embodied in individuals (Polanyi, 2009). Unlike explicit knowledge codified and transmittable in systematic language, tacit knowledge is so deeply rooted in the human mind that it is difficult to codify and communicate and can be acquired only through direct experience, such as observation, imitation, and practice (Polanyi, 2009). Consequently, capabilities can be differentiated via learning experiences that are somewhat idiosyncratic to each individual. This differentiation explains the variation in capability across individuals, a variation that virtual R&D teams seek to bridge or synergistically combine. However, once formed, developing an effective knowledge integration mechanism in which an individual combines their tacit knowledge with others is crucial for effective knowledge-sharing and innovation (Hargadon and Sutton, 1997).

Working and interacting with team members often facilitate knowledge creation through the dynamic process of individual knowledge transcending into organizational knowledge (Nonaka, 1994). Such knowledge integration processes take place primarily through four modes of conversion between the tacit and explicit knowledge dimensions. Tacit-to-tacit conversion (called socialization) takes place when the tacit knowledge of one individual is shared with others through direct experience. On the other hand, tacit-to-explicit conversion (externalization) occurs when an individual or group can articulate the foundations of individual tacit knowledge. Explicit-to-explicit conversion (combination) takes place when an individual or group combines discrete pieces of explicit knowledge into a new whole. Finally, explicit-to-tacit conversion (internalization) takes place when new explicit knowledge is shared throughout the team, and, in turn, team members begin to use it to broaden, extend, and reframe their own tacit knowledge. Such conversion tends to become faster and larger in a spiral process, as more diverse members become involved (Nonaka and Takeuchi, 1995; Argote et al., 2021). Thus, collective individual capabilities residing in a team become the foundation for team capability. We, therefore, propose the following hypothesis:

H1a: *A virtual R&D team's innovative output is a positive function of the sum of the individual capabilities in the team.*

While collective individual capabilities are the building blocks of team capability, this individual knowledge base may be an insufficient condition for a team's innovative performance, given that the collective sum of team members is more than the sum of each. As R&D teams increasingly operate in an international and virtual context, understanding how diversity in the team composition affects innovative performance is becoming more important (Reagans and Zuckerman, 2001). A principal explanation for how diversity in a team might be beneficial is that diverse team members bring a larger pool of information, knowledge, and expertise to the team. In addition, diverse knowledge and expertise within a team can promote learning and search behaviors that, in turn, lead to adaptive and innovative solutions (Van Der Vegt and Bunderson, 2005). Chen et al. (2008) pointed out that R&D project teams have a high level of social interaction because the diverse expertise of their members allows them to tap into a broad array of external information and knowledge and stimulate team creativity. Because sensing and acquiring new knowledge depends on the range and depth of the existing knowledge base, the team with more diverse knowledge groups tends to acquire new knowledge more easily. Virtual R&D teams are, therefore, an attractive organizing option when individuals possess diverse information, knowledge, and expertise that bear on a complex problem or issue. Thus, we propose the following hypothesis:

H1b: *A virtual R&D team's innovative output is a positive function of the diverse expertise of its team members.*

2.3 Social Capital and Innovation

The sum and diversity of individual capabilities present opportunities for effective knowledge-sharing and innovation. However, the existence of complementary knowledge and expertise is a necessary but insufficient condition to achieve synergy. Recent studies go beyond the notion of complementary knowledge and expertise and indicate that the innovative outcomes of R&D teams can be enhanced by developing social capital within a team to manage the R&D project effectively (Breschi and Malerba, 2005; Chen et al., 2008; Lee et al., 2005). This finding is especially true for virtual teams that have developed a notorious reputation not only for being very difficult to manage and costly to execute

(Rosen et al., 2007) but also for having limited time for developing learning experiences within the team. Therefore, we argue that effective knowledge-sharing and innovation in a virtual R&D team will be considered maximized when the team capability aligns with its social capital.

Drawing on Granovetter's (1985) discussion of structural and relational embeddedness, Nahapiet and Ghoshal (1998) suggest that, in addition to structural and relational dimensions, social capital should include a cognitive dimension that refers to the sense-making process among parties. Specifically, the structural dimension of social capital describes the overall pattern of network linkages, the relational dimension describes a history of interactions, and the cognitive dimension describes shared systems of meaning among parties. We posit that each dimension has an important impact on the innovative performance of virtual R&D teams by influencing not only knowledge transfer within the team but also access to external knowledge. Since R&D activities often involve non-repetitive tasks that are inherently ambiguous and complex, working with others, particularly in virtual teams, allows the individual to draw upon the knowledge base of others and, hence, benefit from multiple sources of knowledge and expertise (Reagans and Zuckerman, 2001). We identify external linkages, prior ties, and adaptive learning as the proxies for the structural, relational, and cognitive dimensions of social capital. We then argue that external linkages enable external knowledge acquisition, and both prior ties and adaptive learning facilitate knowledge transfer within the team.

The fundamental notion of social capital theory is that network links provide access to resources (Nahapiet and Ghoshal, 1998). External linkages provide access to external resources, constitute a valuable source of information benefits, and reduce the amount of time required to gather information (Chen et al., 2008). Thus, R&D teams having more external linkages will be more likely to gather useful information and get access to the cutting-edge science and technology developed elsewhere (Fleming et al., 2007; Hargadon and Sutton 1997). External linkages are especially valuable in a virtual R&D setting, in which R&D teams race towards cutting-edge scientific and technological developments and in which a winner-take-all situation often exists (Edmondson and Nembhard, 2009). These studies, when taken together, point to the idea that external linkages are crucial for external knowledge access and new knowledge creation. Thus, we propose the following hypothesis:

H2a: A virtual R&D team's innovative output is a positive function of its external linkages.

The relational dimension of social capital describes the nature of relationships and is, thus, concerned with knowledge about partners and team members (Nahapiet and Ghoshal, 1998). Through the history of working relationships, individuals learn about each other's ways of working and interpret each other's actions based on experiences. Individuals who have worked together in the past will have basic understanding of partner skills and capabilities, which is crucial for effective learning and knowledge creation. As a result, team members with prior working experience can forgo the relationship-building processes necessary for individuals working together for the first time. On the other hand, team members without prior ties must go through a relationship-building period that may intervene with effective learning. This is a process of developing the relational capital that is necessary to create successful working routines. Furthermore, prior ties between individuals can generate an initial base for interpersonal trust (Nahapiet and Ghoshal, 1998). Knowledge is often tacit and difficult to transfer. Relational capital and trust developed through prior working relationships reduce the fear of opportunistic behaviour, allow for greater openness, and, hence, facilitate knowledge transfer within a team (Rosen et al., 2007).

Nahapiet and Ghoshal (1998) pointed out that socially embedded relationships can promote cooperation and facilitate a greater exchange of high-quality information, problem-solving, decision-making, and the generation of ideas. In particular, in a virtual setting, mutual understanding and trust must be established in the start-up phase of an R&D project. Because of the uncertainty inherent in the project that often requires non-routine problem-solving and interpersonal trust, virtual R&D teams are better managed through informal control mechanisms (Gassmann and Von Zedtwitz, 2003; Gillespie et al., 2017; Glikson and Erez, 2019). Furthermore, interpersonal ties among their members are more conducive for problem-solving and innovation (Carmeli and Dothan, 2017; Lee et al., 2005). Thus, we propose the following hypothesis:

H2b: A virtual R&D team's innovative output is a positive function of prior ties among team members.

The cognitive dimension of social capital describes a sense-making process among parties, which begins with joint learning about tasks at hand (Nahapiet and Ghoshal, 1998). Individuals involved in R&D activities need to have a shared understanding of the requirements of R&D tasks to have a common foundation or understanding upon which to act (Kirkman et al., 2004). Since R&D work often involves novel tasks that are inherently ambiguous and complex, individuals who share a mental model with others can also share ideas and information more efficiently and effectively (Van Der Vegt and Bunderson, 2005).

The scope and size of virtual R&D teams change and adapt to the project tasks at hand. Virtual R&D teams are an effective form of organization for first-of-the-kind frontier projects not only because their input may be more diverse but also because they are believed to adapt faster to unexpected change (Marlow et al., 2017). Dealing with uncertainty and ambiguity in frontier projects requires team members to make changes by adapting new internal structures and procedures (Song et al., 2007). In fact, team learning has been captured and defined as a process in which a team takes action, obtains and reflects upon feedback, and makes changes to adapt or improve (Edmondson and Nembhard, 2009). Accordingly, we argue that adaptive learning is crucial for virtual R&D teams because it can promote shared understanding about tasks, and thereby facilitate effective knowledge-sharing and innovation. Thus, we propose the following hypothesis:

H2c: A virtual R&D team's innovative output is a positive function of its adaptive learning.

Ⅲ. Methodology

3.1 Measures

3.1.1 Dependent Variables

In previous studies, the innovative performance of R&D teams has been measured by various indicators, such as the number of new projects developed, the number of product and process innovations, the number of academic papers published, and the number of patents produced (Huang and Chen, 2017; Lee et al., 2005; Mazur and Inków, 2017; Sun et al., 2020). The Frontier R&D Program and its R&D units have evaluated the performance of the individual R&D projects in terms of academic papers published in domestic and international journals and domestic and international patents registered. All the R&D project teams are obligated to report their performance outcomes at the end of each year during the entire project period and for the subsequent two years after project termination.

In this study, the innovative performance of R&D teams is measured by the number of papers and patents produced during the project execution period and the subsequent two years at the project team level. In the annual performance evaluation, the Frontier R&D Program and its R&D units officially assigns a 200% weight to Science Citation Index

(SCI) papers and international patents, as opposed to non-SCI papers and domestic patents. We measured paper and patent publication scores accordingly. The paper publication score is measured by the sum of the total number of domestic journal papers and the 200% weighted total number of international journal papers. The patent publication score is measured by the sum of the total number of domestic patents and the 200% weighted total number of international patents.

3.1.2 Independent Variables

Team capability is measured by two variables: the collective individual capabilities and the expertise diversity of team members. The individual capability is measured by the prior paper and patent publication performance of R&D team members. The prior paper and patent publication records of all participants had been reported in the initial project proposal of each R&D team. We measure individual capability in terms of the prior paper and patent publication performance at the team level. In this regard, we separately counted the numbers of papers and patents published by each project member during the recent three years preceding project participation. The same weighting scheme as the dependent variables is applied. The individual capability score is aggregated at the team level. In the analyses, the prior paper performance is employed as the measure of individual capability when the paper outcome is adopted as the dependent variable, while in the other case, the prior patent performance is introduced as the dependent variable. We used Blau's (1977) index to measure expertise diversity as the diversity of team members' disciplines in their final degree.

Social capital is measured by three variables: external linkages, prior ties, and adaptive learning. The external linkages are measured by the average number of international conferences attended by team members. The number of conference participants multiplied by the number of team member participants is normalized by the team size, i.e., the total number of team members. Prior ties are measured by the number of prior co-authorships and co-inventorships among team members. Furthermore, adaptive learning is measured by the level of changes in R&D objectives and methods. In this regard, it is the ratio of the number of R&D objectives and methods deleted or newly introduced during the entire project period to the total number of R&D objectives and methods submitted at the research proposal stage.

3.1.3 Control Variables

Several control variables are introduced to better capture the hypothesized effects of independent variables on the performances of virtual R&D teams. The budget is the amount of R&D expense used by each R&D project team for the entire project period. The number of organizations measures the total number of organizations affiliated by the team members. Both variables control the effects of project size and complexity on performance. Since there could exist different research orientations and research productivity levels between university and industry researchers, we also controlled the university portion as that of university-affiliated members among all the members of a team. Finally, a bio sector dummy was introduced to control for sectorial variations.

3.2 Sample and Data

This study's research sample reflects the virtual R&D project teams sponsored by the 21st Century Frontier R&D Program, a strategic national R&D program funded by the Korean Ministry of Education, Science, and Technology. The Frontier Program is the representative national long-term, large-scale R&D program in Korea implemented since 1999 with a mission to develop the world's best technology in biotechnology, information technology, nanotechnology, and aeronautics. The Frontier Program has, thus far, enabled the development of numerous high value-added technologies in fields such as nano devices and materials, heavy naphtha decomposition technology, superconductivity technology, microorganism, brain function, and angiography. Furthermore, the technologies developed through the Frontier R&D Program and transferred to companies are estimated to generate a direct economic benefit of KRW 4.98 trillion (about $4.71 billion).

In this study, the unit of analysis is the R&D project team. Forming R&D project teams requires that prospective project leaders recruit project members among the R&D professionals within or outside their respective organizations. To obtain proper matching funds and to win the competition among the research proposals, the prospective project leader should compose the team with the most suitable R&D professionals.

The directors of 16 R&D units in the Frontier R&D Program were initially contacted and requested to participate in this study. The other five R&D units were excluded from the initial contact because there were recently launched. The directors of 11 R&D units provided data for this study, and the author asked them to select six to ten projects within their R&D units that had been terminated. All the historical documents and reports filed for the selected R&D projects were provided, and the collected documents for these projects include research proposals for the Frontier R&D program, initial project execution plans, annual progress reports, annual project execution plans, project final reports, and project outcome lists. The document files for a total of 80 projects were collected. Seven projects out of a total of 80 projects were further excluded because complete data were not provided. Thus, 73 R&D project teams were identified for the statistical analysis.

Ⅳ. Data analysis

4.1 Descriptive statistics

Table 1 shows the descriptive statistics and correlation matrix for all the variables included in this study. Although the means and standard deviations reported in Table 1 are for unstandardized measures, we used the standardized values of all variables except the two dependent variables (paper and patent) to test the hypotheses. Standardization reduces multicollinearity and makes it easy to interpret the results.

The number of papers and patents is a non-negative integer with a limited range and, therefore, violates the assumptions of OLS regression—homoscedastic and normally distributed errors. Under these conditions, Poisson or negative binomial models are appropriate. Unlike the Poisson model, the negative binomial model does not assume the mean-variance equality of the count-dependent variable. We tested for over-dispersion of the two dependent variables and found an over-dispersion feature (the estimates were more than 1.0 and significant). We, thus, employed the negative binomial model in this study. In the negative binomial model, the estimates of the parameters can be calculated in two ways: the maximum likelihood (ML) and quasi-maximum likelihood (QML). Clark (1989) showed that the QML estimator is more accurate than the Therefore, we employed the negative binomial model with QML estimators.

4.2 The Results of the Regression Analyses

Table 2 presents the empirical results of the negative binomial regression with QML on papers. Model 1 is the baseline model with only the control variables. Models 2 and 3 subsequently add the two team capability variables: collective individual capabilities and expertise diversity. The two team capability variables appear statistically significant at the 1% level. Model 4 includes both team capability variables. Models 5-7 subsequently add the three social capital variables: external linkages, prior ties, and adaptive learning. Among these social capital variables, both prior ties and adaptive learning appear statistically significant at the 10% level. Surprisingly, the relationship between prior ties and paper publication turned out negative. However, the significance of the prior ties variable disappears in Model 8, a full model.

〈Table 1〉 Correlations and Descriptive Statistics

Variable	Mean	Std	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Papers	18.315	21.922	1.000												
2. Patents	5.301	7.986	0.325**	1.000											
3. Individual Capability (paper)	2383.00	2316.00	0.389**	-0.077	1.000										
4. Individual Capability (patent)	488.539	514.453	0.022	0.214	0.276*	1.000									
5. Expertise Diversity	0.567	0.268	0.299*	0.129	0.150	0.275*	1.000								
6. External Linkages	26.283	38.289	0.113	0.378**	-0.086	-0.025	0.123	1.000							
7. Prior Ties (paper)	2.849	3.684	-0.059	0.036	0.296*	0.441**	0.324**	-0.059	1.000						
8. Prior Ties (patent)	1.082	2.629	-0.010	0.189	0.159	0.704**	0.287*	-0.036	0.624**	1.000					
9. Adaptive Learning	0.371	0.396	-0.024	0.380**	-0.233*	-0.090	0.065	0.378**	0.008	0.008	1.000				
10. Budget	1008676	804903	0.141	0.532**	-0.174	0.069	0.503**	0.374**	0.099	0.255*	0.218	1.000			
11. Number of Organizations	0.176	0.158	0.157	0.007	-0.100	-0.034	0.450**	-0.045	0.176	0.129	0.234*	0.211	1.000		
12. University portion	57.607	39.218	0.278*	-0.117	0.247*	-0.123	-0.168	0.156	-0.056	-0.269*	-0.013	-0.290*	-0.191	1.000	
13. Bio Sector dummy	0.671	0.473	0.152	-0.190	0.230*	-0.034	-0.238*	-0.203	-0.148	0.011	-0.355**	-0.274*	-0.324**	0.123	1.000

*〈 0.05, **〈 0.01

〈Table 2〉 Results of Negative Binomial Regression on Paper

Variables	M1	M2	M3	M4	M5	M6	M7	M8
Team Capability								
Individual Capability (paper)		1.99(0.70)**		1.66(0.67)*	1.67(0.67)*	1.95(0.68)**	1.77(0.70)**	2.03(0.72)**
Expertise Diversity			1.23(0.41)**	0.85(0.39)*	0.85(0.39)*	0.98(0.39)**	1.00(0.38)**	1.13(0.39)**
Social Capital								
External Linkages					0.16(0.87)			-0.35(0.96)
Prior Ties (paper)						-0.60(0.35)†		-0.56(0.34)
Adaptive Learning							0.85(0.45)†	0.86(0.49)†
Control Variables								
Budget	1.80(0.57)**	1.90(0.55)***	1.18(0.57)*	1.47(0.56)**	1.39(0.65)*	1.58(0.57)**	1.23(0.50)**	1.48(0.64)**
No. of organizations	1.08(0.45)*	0.97(0.44)*	0.67(0.41)	0.69(0.40)*	0.70(0.31)*	0.62(0.39)	0.62(0.40)	0.53(0.38)
University portion	1.00(0.35)**	0.81(0.31)*	0.92(0.33)**	0.79(0.31)*	0.78(0.31)*	0.81(0.29)**	0.82(0.30)**	0.87(0.28)**
Bio Sector dummy	0.84(0.33)*	0.62(0.31)*	0.83(0.30)**	0.66(0.30)*	0.66(0.30)*	0.57(0.29)*	0.86(0.29)**	0.78(0.29)**
Constant	0.83(0.43)†	0.67(0.42)	0.33(0.40)	0.35(0.41)	0.35(0.41)	0.42(0.41)	-0.05(0.42)	-0.00(0.45)
Log-likelihood	-703.117	-610.126	-667.086	-605.842	-699.825	-696.890	-694.627	-568.324
Pseudo R^2	0	0.132	0.051	0.138	0.005	0.009	0.012	0.192

〈Table 2〉 Results of Negative Binomial Regression on Paper
† 〈 0.1, * 〈 0.05, ** 〈 0.01, *** 〈 0.001

〈Table 3〉 Results of Negative Binomial Regression on Patents

Variables	M1	M2	M3	M4	M5	M6	M7	M8
Team Capability								
Individual Capability (patent)		1.75(0.78)*		1.90(0.74)*	2.03(0.79)*	2.24(0.93)*	1.98(0.80)*	2.32(1.00)*
Expertise Diversity			-0.33(0.57)	-0.67(0.53)	-0.66(0.54)	-0.66(0.53)	-0.45(0.55)	-0.46(0.53)
Social Capital								
External Linkages					1.29(0.70)†			0.74(0.70)
Prior Ties (patent)						-0.47(0.74)		-0.39(0.77)
Adaptive Learning							1.27(0.51)*	1.14(0.53)*
Control Variables								
Budget	2.73(0.65)***	2.64(0.65)***	2.88(0.70)***	2.97(0.68)***	2.38(0.64)***	3.00(0.67)***	2.55(0.56)***	2.32(0.62)***
No. of organizations	-0.95(0.51)†	-0.92(0.51)†	-0.87(0.48)†	-0.76(0.47)	-0.58(0.50)	-0.65(0.50)	-0.78(0.49)	-0.59(0.52)
University portion	-0.43(0.37)	-0.38(0.36)	-0.46(0.36)	-0.41(0.36)	-0.56(0.37)	-0.44(0.37)	-0.36(0.37)	-0.46(0.38)
Bio Sector dummy	0.04(0.36)	-0.00(0.36)	0.03(0.36)	-0.03(0.35)	0.06(0.37)	-0.05(0.35)	0.30(0.38)	0.29(0.38)
Constant	1.35(0.48)**	0.99(0.48)*	1.52(0.60)**	1.28(0.54)*	1.18(0.56)*	1.24(0.54)*	0.65(0.63)	0.62(0.64)
Log-likelihood	-317.911	-298.452	-311.991	-285.645	-306.181	-288.705	-313.273	-246.56
Pseudo R^2	0	0.061	0.019	0.101	0.037	0.092	0.015	0.224

† 〈 0.1, * 〈 0.05, ** 〈 0.01, *** 〈 0.001

Table 3 presents the results of the negative binomial regression on patents. In the case of patent publication, the three variables of collective individual capabilities, external linkages, and adaptive learning turned out significant. Although the external linkages variable is statistically significant at the 10% level in Model 5, this significance disappears in Model 8, a full model. For paper publications, the baseline model (M1) reported a log-likelihood of -703.117 with a pseudo R^2 of 0.000. The explanatory power improved steadily across specifications, with the full model (M8) achieving a log-likelihood of -568.324 and a pseudo R^2 of 0.192. For patent production, the baseline model (P1) showed a log-likelihood of -317.911 and a pseudo R^2 of 0.000. The final model (P8) improved markedly, with a log-likelihood of -246.560 and a pseudo R^2 of 0.224.These results indicate that the inclusion of team capability and social capital variables substantially enhances the explanatory power of the models for both papers and patents.

Ⅴ. Discussions

This study aims to investigate the innovative effect of both team capability and social capital in the context of virtual R&D teams. The virtuality embodied in R&D teams has a constraining, as well as an enabling effect to the innovative outcome. The formation of a virtual R&D team is an acknowledgement that team members possess useful knowledge and expertise to contribute to the virtual R&D team. However, without the ability to manage the team, the formation of an R&D team does not ensure that its potential objectives will be achieved. The diverse expertise of team members must be effectively managed and integrated to realize the synergy at the team level. Hence, in addition to assessing the effect of team capability, we also assess the incremental value of social capital to the team's innovative performance, namely, papers and patents produced by the virtual R&D team. Social capital theory provides the theoretical basis for the innovative effects of external linkages, prior ties, and adaptive learning (Chen et al., 2008; Nahapiet and Ghoshal, 1998).

The findings indicate intriguing correlations between team capabilities and the types of innovation they achieve. Academic innovation, as measured by the production of research papers, benefits from both prior capacity and a diverse range of expertise within the team. This suggests that having a broad base of knowledge and skills positively influences the ability to innovate in an academic context.

In contrast, practical innovation, such as the development of patents, does not appear to benefit from diverse expertise. This lack of relationship implies that practical innovations are more reliant on specialized knowledge within specific areas. Patents often focus on specific, narrowly defined technological advances, requiring deep expertise rather than a broad range of skills.

Additionally, practical innovation necessitates stronger external linkages. This means that teams working on patents need to stay informed about the latest developments in their field, often seeking input and information from external sources to drive their innovation. Tracking recent innovations and integrating external insights is crucial for success in practical innovation.

Ⅵ. Conclusion and Implications

6.1 Implication

The empirical test was conducted separately for both innovative outcome variables—papers and patents—because the scholarly scientific paper publication differs from the commercial, technical patent publication. In this regard, a paper describes experimental results, while a patent defines utility and makes claims on inventiveness. Previous studies have also suggested that the incentive structures of the science and technology worlds are distinct (Murray 2002). Science is epitomized by paper publication and supported by a knowledge-based reward system, which contrasts with the world of technology where ideas are produced for economic ends and encoded in patents to facilitate appropriability. Practical implementation

The results provide two main managerial implications. First, using a virtual team for R&D is often a necessity and not a choice. Being "virtual" is, in most cases, not a strategy but an operational reality (Dulebohn and Hoch, 2017; Gassmann and Von Zedtwitz, 2003; Wei et al., 2018). This finding is especially true for a frontier R&D project characterized by inherent ambiguities and uncertainties with respect to the market, technology, and the R&D process (Song et al., 2007). Virtual teams, by nature, rarely exhibit clear team boundaries and uniform role allocations. Such fluid team boundaries allow flexible arrangements for frontier R&D projects but, at the same time, can make collaboration challenging within the teams. Therefore, managing the dilemma between operational flexibility and managerial challenges for facilitating innovative performance in virtual R&D teams is a critical issue for project managers. Second, in the virtual team context, the quality and quantity of knowledge-sharing is influenced by the levels of social capital among team members. However, as our result with the prior ties variable indicates, there is a downside to relational embeddedness. Our results indicate that prior ties do not exert a strong positive influence on paper publications; rather, the coefficients are negative and only marginally significant in some models. This suggests that while repeated collaborations may provide efficiency benefits, they do not necessarily translate into enhanced academic outputs. One explanation is the problem of over embeddedness (Uzzi, 1997), whereby reliance on existing ties reduces access to non-redundant knowledge and fresh perspectives. As Gargiulo and Benassi (2000) argue, such network closure can reinforce routine collaboration patterns at the expense of creativity. Accordingly, our findings point to the importance of balancing the trust and coordination benefits of prior ties with the need for novel linkages that stimulate new ideas.

The search for co-workers is likely to be guided by socially embedded relationships. Because developing a new relationship is an arduous endeavour, project managers in charge tend to rely on existing relationships to set up virtual R&D teams. This approach may be practical but not optimal since too much relational embeddedness could limit the opportunities for tapping into the diverse knowledge, expertise, and experience that new members can offer. The primary role of project managers is to strive to ensure expertise diversity among team members. However, to function at their full potential, virtual teams must develop routines enabling team members to tap into this expertise, experience, and knowledge of their teammates, as needed (Rosen et al., 2007).

6.2 Conclusion

The results indicate that, overall, the team capability variables have a positive impact on the innovative performance of the virtual R&D team. The collective individual capability variable has the greatest positive effect on both paper and patent publications. Apparently, collective individual capabilities provide the foundation for team-level capability. The expertise diversity variable is significant and positive only on paper publications, indicating that, especially where performance is rewarded for epistemic reasons, diversity in the expertise of team members provides the potential opportunity for individual members to add on diverse fields of knowledge and build up to the team-level capability. However, the diversity within the team's expertise may have no, or a negative, effect on technological innovation for economic ends (Edmondson and Nembhard, 2009).The process of practical innovation (e.g., patents) is the context within which information and knowledge is integrated from different industries and locations. Thus, diverse team members may hinder the integration of heterogenous knowledge (Mors, 2010).

Among the social capital variables, adaptive learning has the greatest positive effect on the paper and patent publications of virtual R&D teams. Adaptive learning in the R&D process refers to the sense-making effort to understand an emergent reality, provide meaning to new data and information, and adjust existing project goals and methods accordingly (Eisenhardt and Tabrizi, 1995). In fact, adaptive learning underlies the rationale for virtual R&D teams. When uncertainty reigns, a virtual setting will foster constructive tensions reconciled through adaptive learning processes, resulting in innovative outcomes. Particularly in Frontier R&D Program projects, adaptive learning through a formal project review process is effective in checking current progress against evolving and uncertain markets and technologies (Song et al., 2007). Moreover, frontier R&D projects have little previous available relevant experience by which the project should be structured (Gassmann and Von Zedtwitz, 2003). With increasing knowledge and experience in the course of the project, related goals and methods are increasingly delineated.

Consistent with findings from R&D alliances in patent-intensive industries, such as the pharmaceuticals and biotechnology industries (Powell et al., 1996), the external linkages variable turned out positive and significant on patent publication, albeit marginal. Notably, its significance disappeared when it was added to the model together with other social capital variables. Nonetheless, it seems that social capital in the form of strengthening the external linkages to cutting-edge scientific knowledge and technology may be the way for the virtual R&D team to enhance its inventiveness or improve the chances of producing more patents. However, contrary to our social capital hypothesis, the prior ties variable turned out negative and significant for paper publications, albeit marginal. We suspect that the relational capital arguments, which focus mainly on the ease of knowledge sharing based on the prior partnering experience, may be over-emphasized. If we combine this finding with findings regarding expertise diversity, we could suggest that enhanced relational embeddedness that cannot come along with the diverse learning opportunity may have an adverse effect on paper publications.

The limitations associated with the team-level measurement in this study must be acknowledged. This study aimed to investigate the impact of team level attributes, such as team capability and social capital on the team's innovative performance. However, the small observation number of our team-level data prevented us from examining other possible model specifications, for example, the interactive effects between the team capability and social capital variables. Furthermore, due to few commercialization cases in frontier R&D programs, this study instead captured innovative performance by counting papers and patents produced by the teams. Also, the sample is drawn from Korean government-funded R&D programs, which may differ in structure, incentives, and resource allocation from industry-based virtual teams. Accordingly, caution should be exercised in generalizing the findings, and future research would benefit from examining industry-driven or cross-national samples to validate and extend these results.

In summary, the innovative performance of virtual R&D teams is largely a function of selecting team members with diverse and complementary knowledge, expertise, and experience, as well as enhancing social capital among team members. The contribution of this paper is to examine the incremental value of social capital to innovative performance in a virtual team context, especially in phases of frontier R&D. Among social capital variables, adaptive learning shows the most salient and robust impact on virtual R&D team performance. Virtual team leaders must be able to frame frontier R&D projects as an adaptive learning process where the goals and methods of the projects are reviewed and adapted systematically to emergent internal and external circumstances.

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