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INTER-ORGANIZATIONAL RELATIONSHIPS MANAGEMENT AS A KNOWLEDGE STRATEGY: A SIMULATION APPROACH

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Abstract

Firms absorb knowledge from their partners, make it their own, and use it for innovation. The knowledge performance of a firm embedded in an inter-organizational network can vary depending on how concentrated its ties are and the number of direct ties. This study used an agent-based model and the organizational learning curve theory as basis to show that the knowledge performance of firms can be modified by the way in which the structural factors of an ego network are managed. In particular, the concentration of tie strength decreases the average level of a firm's knowledge profile; that is, a firm's knowledge level decreases when it has strong ties with a particular firm and weak links with others. The number of direct ties, the so-called node degree, increases the diversity of knowledge in the long run. The cumulative knowledge reduction effect of the concentration of tie strength varies depending on the network type. In a random network, the average knowledge reduction effect is mitigated by a high absorptive capacity, whereas the reduction effect is strengthened in a scale-free network. A knowledge strategy is presented to assist firms in effectively accumulating knowledge toward sustainable growth.

Keywords*: inter-organizational network, concentration of tie strength, node degree, knowledge performance, agent-based model*

1. INTRODUCTION

Knowledge is a source of technological innovation. A firm obtains knowledge through its inter-organizational networks. Firms innovate not only by their own internal research and development but also by acquiring skills, knowledge, and information from other firms through partnerships (Choi, 2020). In particular, firms in rapidly developing industries, such as the biotechnology and information and communications industries, strive to secure resources and reduce uncertainty through a variety of cooperative relationships, such as strategic alliances, consortiums, and joint ventures (Hoffmann, 2007). Firms drive innovation through a distributed process based on knowledge flows across organizational boundaries, so-called open innovation (Chesbrough and Bogers, 2014). According to the relational view (Dyer & Singh, 1998), business-to-business relationships can be an important component of a firm's competitive advantage and can lead to better performance. To successfully implement a firm's strategy, it is not possible to rely solely on one relationship. Strategies for accessing a variety of external resources through partnerships in different ways with different partners can be useful. How a set of relationships, rather than one relationship, is created and managed determines a firm's knowledge performance (Hoffmann, 2007).

Identifying the relationship between network structure and innovation performance has been a major concern for management. A knowledge-sharing network that facilitates knowledge exchanges between a central firm and its allied partners can be a source of competitive advantage for a firm (Dyer & Hatch, 2004). The type of network relationship appropriate for a firm has been debated widely because maintaining relationships with multiple partners can be costly (Lavie, 2007). Following Ahuja (2000), this study defines an inter-organizational tie as a voluntary arrangement between independent organizations to share knowledge. The influence of tie strength on knowledge performance has been discussed mainly at a dyad level. If the trust and communication frequency between two firms is high, they are said to be connected by a strong tie. A strong tie facilitates the flow of sensitive and high-level information (Rowley, Behrens & Krackhardt, 2000), but a weak tie allows access to new and diverse information (Hansen, 1999). However, in the ego network of a firm composed of multiple ties, weak and strong connections exist together. If there are multiple ties together, how does the distribution of the relationships relate to knowledge performance? To our knowledge, few studies have revealed the relationship between tie strength distribution and knowledge performance in the presence of multiple ties. This study focuses on the concentration of a firm's tie strength when several ties exist and identifies the relationship between the concentration and knowledge performance.

This study investigates how the structural factors of an ego network affect knowledge performance. Specifically, it argues that knowledge performance can vary depending on tie-strength concentration and the number of direct ties. To this end, an organizational learning model, in which knowledge is exchanged through a network, was built as an agent-based model. Each firm is set to accumulate knowledge by developing knowledge internally and by absorbing knowledge externally in situations in which multiple knowledge domains exist. A simulation revealed that the higher (lower) the tie strength concentration, the lower (higher) is the average level of knowledge. If the number of direct ties is large, the diversity in knowledge domains increases. The average reduction effect of the tie-strength concentration and the increase effect of changes in the number of direct ties vary depending on the network topology or a firm's absorptive capacity.

The contributions of this study are as follows. First, we identified the relationship between structural factors and knowledge performance. We developed a dynamic model that comprehensively considers firm-, relationship-, and network-level factors to clarify the relationship between structural factors and performance in various environments. Second, we present an inter-organizational relationships management framework as a knowledge strategy. Based on the relationship between structural elements and knowledge performance, we provide practical implications by presenting a relationship management plan that fits the objective pursued by each firm.

This paper is organized as follows. Section 2 summarizes previous research related to this study, and Section 3 presents an agent-based model for knowledge diffusion in an inter-organizational network. Section 4 analyses the experimental results. Section 5 discusses the results and presents a knowledge strategy framework. Finally, Section 6 summarizes the findings and outlines the limitations and the direction of future research.

2. LITERATURE REVIEW

Phelps, Heidl, and Wadhwa (2012) defined knowledge networks as networks consisting of nodes, which is the repository of knowledge. The nodes can be either firms or individuals that create, search, assimilate, and exploit knowledge. The performance of the knowledge network varies according to various factors in the network (Al-Jabri & Al-Busaid, 2018). Phelps et al. (2012) classified structural, relational, nodal, and knowledge properties as the main elements. Structural elements relate to how the relationships are connected—where they are located in the network, how they are connected with directly connected partners, what kind of relations exist among the partners, and what form the whole network takes. These structural factors can affect knowledge performance. Node degree is the number of direct ties of an incident to a node (Borgatti, Everett & Johnson, 2013). In studying the relationship between node degree and performance, Ahuja (2000) argued that the higher the number of direct ties, the higher is the innovation performance. A large number of direct links can lead to higher innovation performance due to knowledge sharing, complementarity, and economies of scale. Burt (1992) proposed the concept of a structural hole and argued that if the focal firm's partners were not connected with each other, the information power of the focal firm would be higher. Empirical studies have shown that structural holes improve knowledge performance (Baum, Calabrese & Silverman, 2000; McEvily & Zaheer, 1999), whereas other studies have found that without structural holes, innovation improves (Ahuja, 2000; Schilling & Phelps, 2007). Chen, Zhang, Zhu, and Mu (2020) suggested that the impact pattern of the network positions of organizations on their performance likely varies with the network structure and composition in different inter-organizational contexts. Specifically, they argued that the node degree and structural hole of the research institute respectively affect the performance in an inverted U-shaped manner and in a positive linear manner in the homogeneous university-researcher collaboration network, but have different relationships in the other types of collaboration networks. In addition, the whole network topology can affect the firm's knowledge performance. Network topology refers to a structure of how firms are connected. Typical network topologies include random (Erdős & Rényi, 1959), small-world (Watts & Strogatz, 1998), and scale-free (Barabási & Albert, 1999) networks. A random network refers to a network in which nodes are randomly connected. A regular network refers to a network that is regularly connected to its partners. A small-world network can be constructed by creating a regular network and randomly selecting a small number of links and connecting them to other nodes. A scale-free network is a network in which the degree distribution of nodes follows a power law. The diversity of information can be increased by becoming a ”small world” because there is a shortcut between dense groups (Schilling & Phelps, 2007). Using an agent-based model, Kim and Park (2009) argued that small-world networks are more efficient in diffusing knowledge than are regular or random networks.

Relational elements refer to the type of relationship each node has. A representative example is tie strength. The relationship between two firms is classified as strong or weak based on the tie strength. In a relationship with a strong tie, firms frequently communicate with each other based on trust, intimacy, and reciprocity, whereas in a relationship with a weak tie, firms are remote from each other or occasionally communicate and exchange information (Capaldo, 2007; Granovetter, 1973). Based on the level of intimacy and reciprocity, two firms with a strong tie can share more sensitive information and tacit knowledge than those with weak ties (Granovetter, 1973; Marsden, 1984). Strong ties, as a medium for reliable information delivery, promote the flow of a stream of advanced information and refined knowledge (Rowley et al., 2000). However, an advantage of a weak tie is that it enables access to new and diverse information (Hansen, 1999). Franco and Esteves (2020) argued that weak ties between clusters—groups connected by strong ties—play an important role in knowledge transfer among inter-cluster networks. Studies conducted from a social capital perspective state that links with other firms positively affects a firm's knowledge performance (Carey, Lawson & Krause, 2011). Cousins, Handfield, Lawson, and Petersen (2006) argued that enhancing social relationships between suppliers and buyers contribute to the formation of relational capital, making communication between firms smoother. Dyer and Singh (1998) argued that ties between two firms lead to investments in idiosyncratic assets, which promotes the flow of knowledge. Furthermore, they emphasized that this increase in investment and the facilitation of knowledge flows develop into a self-enforcing structure that further strengthens the tie between the two. Idrees, Vasconcelos, and Ellis (2018) argued that a cooperative–competitive tension of dyadic relationships facilitated knowledge sharing between five-star hotels.

Nodal properties refer to a firm's own characteristics. For example, a firm's high absorptive capacity (Cohen & Levinthal, 1990) facilitates the easy absorption of knowledge from partners (Zhao & Anand, 2009). Xie, Wang, and Zeng (2018) found that absorptive capacity mediated the relationship between inter-organizational knowledge acquisition and firms' innovation performance. Lastly, knowledge performance can vary according to various properties of knowledge. Codified knowledge is more likely to diffuse (Simonin, 1999), and complex and tacit knowledge is difficult to absorb, which can be alleviated by frequent communication (McEvily & Marcus, 2005). According to Balle, Steffen, Curado, and Oliveira (2019), managerial knowledge can be transferred in more alternative ways than technical knowledge.

3. MODEL

The knowledge diffusion model sets a firm as one agent, and each agent corresponds to a node in the knowledge network. Nodes are connected to each other by ties. The diffusion of knowledge occurs between firms linked by a tie. One tie could be a purchase contract, joint research, or joint development. This knowledge diffusion model is based on the work of Kim and Park (2009), but is extended to various network topologies and modified in knowledge acquisition logic. The network topologies considered in this simulation are random, small-world, and scale-free networks. It is assumed that all firms are connected as one network, which means that there are no isolated firms. A scale-free network is made using a preferential attachment, as proposed by Barabási and Albert (1999). The preferential attachment method starts from one link and adds a node with a fixed number of links (PA-degree) to connect them. When a new node is added to an existing node, it is added probabilistically in proportion to how many links the existing node has.

The organizational learning theory was developed by Argote and colleagues, and many empirical studies have been conducted based on it (Argote, 2013; Argote, Beckman & Epple, 1990; Epple, Argote & Devadas, 1991; Epple & Argote, 1996; Epple, Argote & Murphy, 1996). Based on those previous studies, this study models the way in which a firm accumulates knowledge assets based on the organizational learning curve equation suggested by Epple et al. (1991). A firm's knowledge assets are represented by a single knowledge profile (KP), and a knowledge profile consists of multiple knowledge domains. It is assumed that all companies build knowledge in a knowledge profile consisting of the same D knowledge domains. Each firm accumulates knowledge in two ways. One is through research and development inside the firm itself, and the other is by absorbing the knowledge of partners tied with the firm. Based on Epple et al.'s (1991) organizational learning curve equation, the equation for accumulating knowledge is as follows:

$$k_{id,t} = \alpha_i K_{id,t}^{\lambda_i} + \beta_i \max\,[K_{jd,t} - K_{id,t}, 0] \qquad (1)$$

where $k_{id,t}$ is the increment of knowledge accumulated in knowledge domain d at time t by firm i, and $K_{id,t}$ is the cumulative level of knowledge accumulated in knowledge domain d at time t by firm i. The first term on the right-hand side is the knowledge gained through research and development inside the firm; α_i denotes a firm's internal innovation capability, which is the capability obtained through internal research based on the firm's accumulated knowledge. The larger α_i is, the greater is the internal research capability that firm i can create by using existing accumulated knowledge. In Equation (1), λ_i is the coefficient of the effect of the learning curve of firm i. The larger λ_i is, the greater is the learning ability that can be generated through existing knowledge. The second term on the right-hand side is the other source from which firms can build their knowledge and absorb knowledge of partners connected to them for their own knowledge enhancement; β_i is firm i's absorptive capacity (Cohen & Levinthal, 1990). If the partner firm's knowledge concerning the knowledge domain is greater, the focal firm absorbs the knowledge gap multiplied by β_i. Among the partner firms that are connected to the firm, firm j is probabilistically selected to absorb such knowledge. The probability p_{ij} that firm i selects partner firm j as a source of knowledge is made proportional to the tie strength as follows:

$$p_{ij} = \frac{s_{ij}}{\sum_{j \in N(i)} s_{ij}} \qquad (2)$$

where s_{ij} refers to the tie strength of firms i and j, and $N(i)$ is the set of partners directly connected to firm i. However, some of the knowledge of a firm disappears or becomes obsolete over time (Epple et al., 1996). Thus, the cumulative level of knowledge of firm i, considering the depreciation of this knowledge, is

$$K_{id,t+1} = (1-\delta)K_{id,t} + k_{id,t} = (1-\delta)K_{id,t} + \alpha_i K_{id,t}^{\lambda_i} + \beta_i \max\,[K_{jd,t} - K_{id,t}, 0] \qquad (3)$$

where δ denotes the depreciation rate of knowledge, which is the rate at which knowledge becomes obsolete from the cumulative knowledge in the previous period. In industries with rapid innovation and change, the value of δ is relatively large, and in industries in which technology has reached maturity, the value is relatively small. Equation (3) states that the knowledge of firm i at time t + 1 decreases at the depreciation rate of the cumulative knowledge at the previous time, increases in proportion to the internal capability of the company, and finally increases by absorption of knowledge outside the firm. The equation encompasses the entire life cycle of knowledge by including two sources of knowledge growth and the depreciation of knowledge.

The explanatory variable, tie-strength concentration, is measured by Herfindahl–Hirschman Index (HHI). The concentration of firm i's tie-strength is defined as follows:

$$\mathrm{HHI_i} = \sum_{j \in N(i)} s_{ij}^2 \tag{4}$$

The HHI has a maximum value of 1, and the larger the value, the more concentrated is the tie-strength. Another explanatory variable—node degree—is defined as the number of direct ties connected to each node (Newman, 2010).

The dependent variables are KPMean and KPStdev. KPMean is the arithmetic mean of all knowledge domains in a knowledge profile, and KPStdev is the standard deviation, as shown in the following equations:

$$\mathrm{KPMean_{i,t}} = \frac{1}{D}\sum_{d=1}^{D} K_{id,t} \tag{5}$$

$$\mathrm{KPStdev_{i,t}} = \sqrt{\frac{1}{D-1}\sum_{d=1}^{D}\left(K_{id,t} - \mathrm{KPMean_{i,t}}\right)^2} \tag{6}$$

The network used in this model consists of 100 nodes. The parameters used in the model are designated as random variables, as summarized in Table 1, with reference to Kim & Park (2009), to allow for the heterogeneity of firms. Fifty repetition experiments were performed on one network topology. Simulations were performed up to 10,000 ticks, at which the cumulative knowledge of all nodes was stable. Short-term (100 ticks) and long-term (10,000 ticks) data were collected. The agent-based model presented in this study was implemented using NetLogo 6.1.1 (Wilensky, 1999), and the simulation experiment used the BehaviorSpace tool built into NetLogo.

4. RESULTS

A hierarchical regression analysis was performed, estimated by the following equations:

$$\widehat{KPMean_i} = \widehat{\beta_0} + \widehat{\beta_1}\alpha_i + \widehat{\beta_2}\beta_i + \widehat{\beta_3}\lambda_i + \widehat{\beta_4}HHI_i + \widehat{\beta_5}HHI_i\times\alpha_i + \widehat{\beta_6}HHI_i\times\beta_i + \widehat{\beta_7}HHI_i\times\lambda_i \tag{7}$$

$$\widehat{KPStdev_i} = \widehat{\beta_0} + \widehat{\beta_1}\alpha_i + \widehat{\beta_2}\beta_i + \widehat{\beta_3}\lambda_i + \widehat{\beta_4}Degree_i + \widehat{\beta_5}Degree_i\times\alpha_i + \widehat{\beta_6}Degree_i\times\beta_i + \widehat{\beta_7}Degree_i\times\lambda_i \tag{8}$$

The standardized coefficients and significance level of each variable obtained as a result of the regression analysis are summarized in Tables 2 and 3.

Table 1: Parameters for simulation.

Parameter	Description	Value or Distribution
α_i	Knowledge development capability of firm i	$\sim U[0, \alpha_{max}]$
α_{max}	Maximum value of α_i	0.002
β_i	Absorptive capacity of firm i	$\sim U[0, \beta_{max}]$
β_{max}	Maximum value of β_i	0.2
$K_{id,0}$	Initial value of knowledge domain d of firm i	$\sim U[0, K_{max}]$
K_{max}	Maximum value of $K_{id,0}$	0.1
λ_i	Learning rate of firm i	$\sim U[0, \lambda_{max}]$
λ_{max}	Maximum value of λ_i	0.05
δ	Depreciation rate of knowledge	0.001
s_{ij}	Tie strength of firm i and j	$\sim U[0,1]$
KDnum	Number of knowledge domains	10
PA-degree	Number of links created by one node in preferential attachment	3

Table 2: Results of the hierarchical regression analysis for KPMean

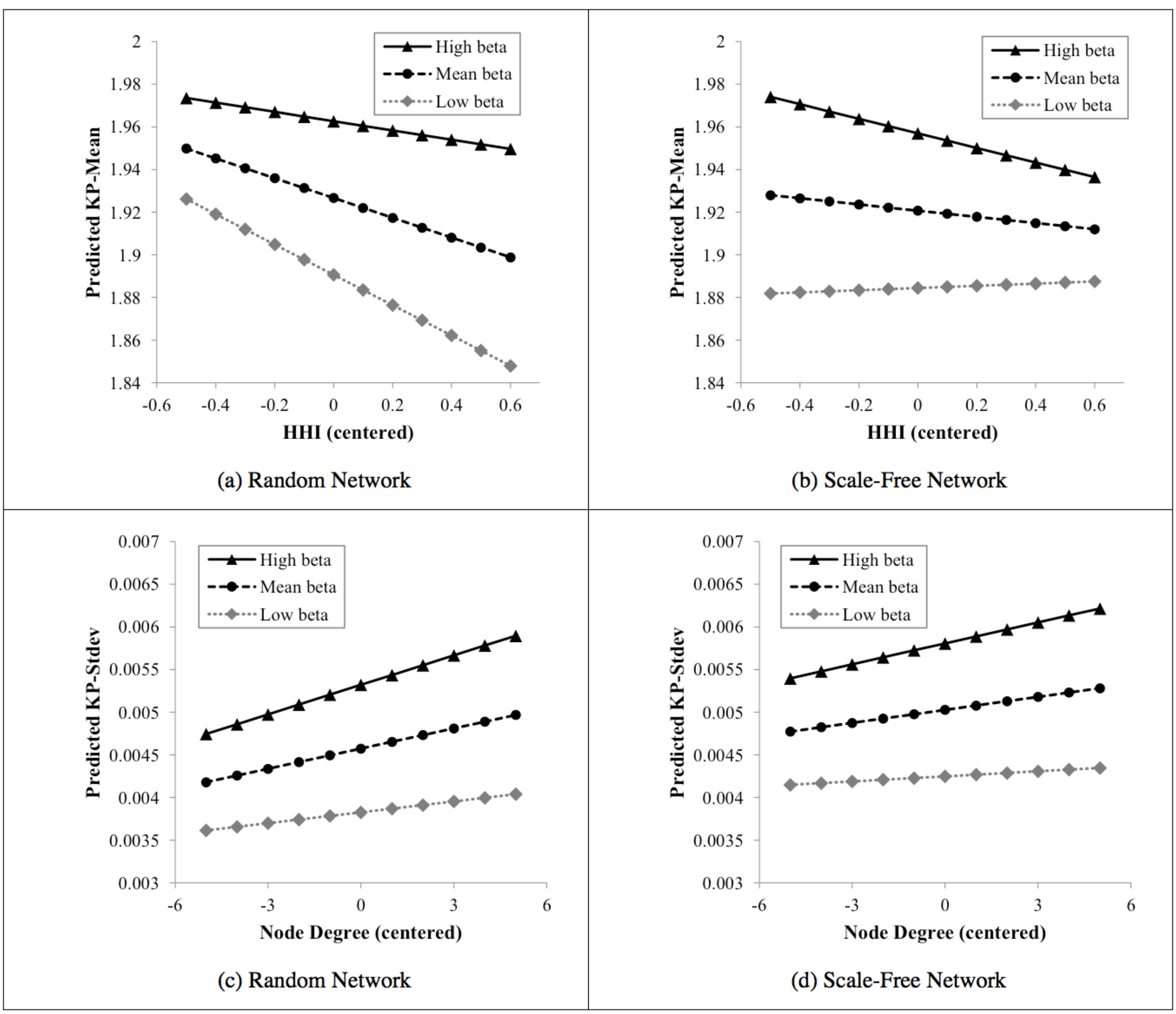
Ticks = 100	Dependent Variable = KPMean											
Topology	Random				Small-World				Scale-Free			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
Alpha	0.590	***	0.591	***	0.636	***	0.636	***	0.584	***	0.584	***
Beta	0.564	***	0.564	***	0.495	***	0.496	***	0.529	***	0.530	***
Learning	−0.028	***	−0.029	***	−0.051	***	−0.052	***	−0.019	*	−0.019	*
HHI	−0.050	***	−0.051	***	−0.034	***	−0.035	***	−0.048	***	−0.050	***
HHI×Alpha			0.004				0.011				−0.036	***
HHI×Beta			−0.010				−0.021	*			−0.038	***
HHI×Learning			−0.031	***			0.005				0.012	
Adj. R^2	0.677		0.678		0.635		0.635		0.636		0.639	
F	2619.323	***	1503.098	***	2172.542	***	1243.896	***	2187.799	***	1265.444	***
F change			5.454	***			2.716	*			13.586	***
Ticks = 10,000	Dependent Variable = KPMean											
Topology	Random				Small-World				Scale-Free			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
Alpha	0.311	***	0.312	***	0.321	***	0.321	***	0.301	***	0.301	***
Beta	0.410	***	0.410	***	0.331	***	0.331	***	0.403	***	0.404	***
Learning	0.014		0.013		0.005		0.005		0.018		0.017	
HHI	−0.045	***	−0.047	***	−0.021	+	−0.021	+	−0.025	*	−0.027	*
HHI×Alpha			0.013				0.001				−0.043	***
HHI×Beta			0.025	*			−0.006				−0.035	**
HHI×Learning			−0.045	***			0.006				0.000	
Adj. R^2	0.270		0.272		0.205		0.205		0.258		0.261	
F	463.465	***	268.300	***	323.770	***	184.982	***	436.041	***	252.961	***
F change			6.164	***			.151				6.822	***

*Notes: Standardized coefficients are presented. ***, **, *, and + denote significance at the 0.1%, 1%, 5%, and 10% levels, respectively.*

For the dependent variable KPMean, Model 1 included only internal development capability (Alpha), absorptive capacity (Beta), learning curve effect (Learning), and HHI; Model 2 added interaction terms between HHI and other variables. In the short term (100 ticks), Model 1 had significant coefficients for all variables in all topologies. In particular, Alpha and Beta were positive, and Learning and HHI were negative. This confirms that HHI has the effect of decreasing the average of KP. Model 2, which added interaction terms, had different results depending on the network topology. In the random network, the coefficient of $HHI_i \times \lambda_i$ was significant and negative ($\widehat{\beta_7}$ = -0.031, p < 0.001). This means that HHI reduces the average of KP, but the higher the learning rate, the stronger is the effect. In the small-world network, the coefficient of $HHI_i \times \beta_i$ was significant and negative ($\widehat{\beta_6}$ = -0.021 , p < 0.05). This means that the HHI's KP average reduction effect is enhanced as the absorptive capacity increases. In the scale-free network, the coefficients of $HHI_i \times \alpha_i$ and $HHI_i \times \beta_i$ were significant and negative ($\widehat{\beta_5}$ = -0.036, p < 0.001; $\widehat{\beta_6}$ = -0.038, p < 0.001). This confirms that HHI's KP average reduction effect can vary depending on the internal development and absorptive capacity. In short, the results indicate that the short-term KP average level decreases as the HHI increases, and that the moderating effect of the firm's capabilities differs depending on the topology.

The results for 10,000 ticks (long term) were as follows. First, the results differed from those in the short term in that the learning curve effect was not significant. The reduction effect of HHI still was significant in the long term, although marginally significant in small-world networks. Unlike the results in the short term, the moderation effect of absorptive capacity appeared in the random network, in which the coefficient of in the long term was positive and significant ($\widehat{\beta_6}$= 0.025, p < 0.05). This means that in the long term, HHI's KP average reduction effect can be mitigated by the absorptive capacity. Figure 1(a), drawn according to the guidelines of Cohen, Cohen, West, and Aiken (2002), shows how the KP reduction effect of HHI is affected by a high (average + standard deviation), average, and low (average − standard deviation) level of the moderating variable. If the absorptive capacity is large, the reduction effect is mitigated. In the scale-free net-

Figure 1: The moderation effect of absorptive capacity in the long term



work, the short- and long-term scenarios had almost similar effects. In particular, the coefficient for the moderating effect of absorptive capacity was significant and negative. This means that the higher the absorptive capacity, the stronger is the reduction effect of HHI. This is confirmed in Figure 1(b). In firms with low absorptive capacity, HHI's KP average reduction effect may lead to an increase effect on the KP average. This would mean that firms with low absorptive capacity are not significantly affected by the high concentration of relationships in the scale-free networks.

For KPStdev, in the short term (100 ticks) the coefficients of Alpha, Beta, and Degree were significant in Model 1, which considered only main effects. The coefficients of Alpha and Beta were positive,

Table 3: Results of the hierarchical regression analysis for KPStdev

Ticks = 100	Dependent Variable = KPStdev											
Topology	Random				Small-World				Scale-Free			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
Alpha	0.390	***	0.390	***	0.243	***	0.243	***	0.371	***	0.371	***
Beta	0.306	***	0.307	***	0.386	***	0.386	***	0.244	***	0.245	***
Learning	−0.011		−0.011		−0.001		−0.001		−0.011		−0.011	
Degree	−0.119	***	−0.119	***	−0.032	*	−0.034	**	−0.131	***	−0.131	***
Degree×Alpha			0.000				0.014				−0.005	
Degree×Beta			0.029	*			−0.027	*			0.014	
Degree×Learning			0.019				0.009				0.008	
Adj. R^2	0.262		0.263		0.202		0.203		0.219		0.219	
F	445.677	***	256.142	***	317.686	***	182.663	***	351.386	***	200.992	***
F change			2.790	*			2.301	+			.584	
Ticks = 10,000	Dependent Variable = KPStdev											
Topology	Random				Small-World				Scale-Free			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
Alpha	−0.433	***	−0.433	***	−0.445	***	−0.445	***	−0.392	***	−0.391	***
Beta	0.286	***	0.287	***	0.207	***	0.207	***	0.270	***	0.271	***
Learning	0.007		0.007		−0.001		−0.001		−0.001		−0.002	
Degree	0.051	***	0.052	***	0.038	**	0.038	**	0.083	***	0.084	***
Degree×Alpha			−0.047	***			−0.020	+			−0.014	
Degree×Beta			0.025	*			−0.003				0.050	***
Degree×Learning			0.024	*			−0.009				0.016	
Adj. R^2	0.267		0.270		0.248		0.248		0.227		0.230	
F	457.135	***	265.350	***	412.803	***	236.396	***	368.872	***	214.149	***
F change			7.322	***			1.141				6.288	***

*Notes: Standardized coefficients are presented. ***, **, *, and + denote significance at the 0.1%, 1%, 5%, and 10% levels, respectively.*

and the coefficient of node degree was negative and significant in all topologies. This confirms that various knowledge domains are learned evenly in the early stages, because the number of direct relationships is much higher. In the random network, the larger the absorptive capacity, the more the reduction effect on the KP standard deviation of the node degree was mitigated, whereas the reduction effect was strengthened in the small-world network.

As time passed, the reduction effect on the KP standard deviation of the node degree changed to an increase effect. The coefficients of the node degree all changed to positive and were significant. In other words, the more connected firms are, the more diverse their knowledge base becomes. In the random and scale-free networks, the increase effect was strengthened by the absorptive capacity. These results are confirmed by Figures 1(c) and 1(d).

5. DISCUSSION

5.1 Tie-strength concentration and node degree

Firms' decision-making and behavior are affected by how much they depend on their resources and their constraints (Pfeffer & Salancik, 2003). If only a small number of firms in a network have access to resources, their dependence on resources is intensified (Pfeffer & Salancik, 2003). The deeper the dependence on resources, the higher is the interdependence between firms (Burt, 1983). Interdependence between firms enhances the strength of ties. In ties that have been strengthened, knowledge can be effectively transferred with little effort. Especially in the case of tacit or complex knowledge, it is easy to communicate when there are strong ties (Uzzi, 1997). However, strong ties also can cause two firms to become stuck (Lechner, Frankenberger & Floyd, 2010), fall into collective blindness (Nahapiet & Ghoshal, 1998), or become complacent (Villena, Revilla & Choi, 2011), which may hinder the acquisition of knowledge. Moreover, when there is only a limited range of knowledge, knowledge that can be learned from a partner with whom a firm has a strong tie is quickly exhausted. In other words, if firms communicate frequently with each other, new knowledge that can be learned from partners inevitably will decrease, as knowledge is learned before it is accumulated internally and becomes part of the capabilities of the firm. Meanwhile, if the tie strength is not concentrated and is distributed evenly, the partner firms have time to accumulate knowledge by developing their internal capabilities. Therefore, the less concentrated the tie strength, the greater the cumulative knowledge of a firm becomes.

This finding is consistent among all network topologies. However, the moderating effect of absorptive capacity varies depending on the network topology. In a random network, the reduction effect of concentration is alleviated, but in a scale-free network, the reduction effect is strengthened further. This result occurs due to the characteristics of the network topology. Compared with random networks, scale-free networks have a hub-and-spoke structure, so one firm is likely to be connected to a hub. Firms with high absorptive capacity depend more on the knowledge profile of the hub than do firms with low absorptive capacity. As a result, the reduction effect of the tie-strength concentration is further enhanced.

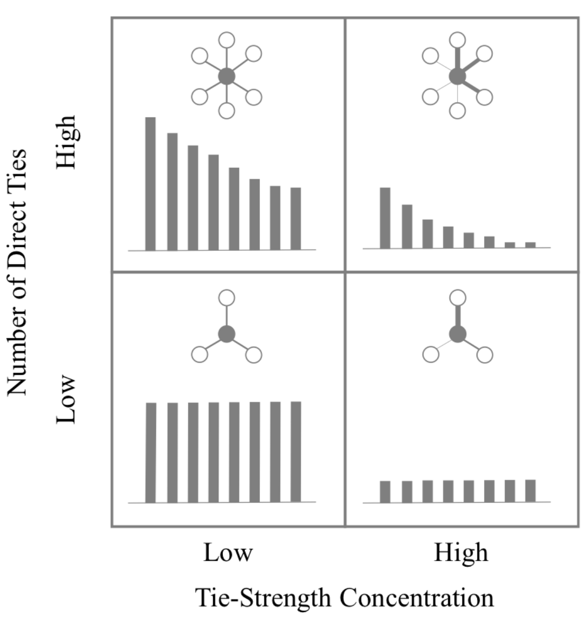
A direct tie can have a positive effect on knowledge performance and a negative effect as well. The larger the number of direct ties, the more likely it is that knowledge will be exchanged with various firms, which would enable a firm to broaden its knowledge profile to various domains (Ahuja, 2000; Owen-Smith & Powell, 2004). However, maintaining too many relationships may cost more than the benefit generated from it (Rothaermel & Alexandre, 2009). With regard to achieving a knowledge profile that encompasses multiple domains, various sources exist for knowledge accumulation. In the short term, diversity in knowledge domains is low as a firm connects with multiple sources, but in the long term, the diversity of knowledge increases. In the setting of the experiment, all firms start with only one knowledge domain which is randomly chosen. In the short term, the more a firm is connected with multiple partners, the more it can accumulate knowledge stocks in diverse knowledge domains, so the deviation among knowledge domains decreases. As time passes, each firm can increase exponentially the knowledge level of some specific knowledge domains according to its internal innovation capability and learning curve effect (Epple et al., 1991). In firms which are more connected with these various partners in terms of knowledge profile, the deviation among knowledge domains increases. This phenomenon has been confirmed by several empirical studies about strategic alliances in the biotechnology industry (e.g., Xu & Cavusgil, 2019; Zhang, Baden-Fuller & Mangematin, 2007).

These results help resolve the conflicting results regarding node degree and performance. Whereas some researchers (e.g., Ahuja, 2000) argued that the higher node degree made its innovation performance greater, others (e.g., Rothaermel & Alexandre, 2009) suggested that increasing reliance on partners has a negative effect on knowledge performance. The present finding suggests that the number of direct ties with suppliers has positive or negative effects, which can change depending on the period. This was revealed by comparing the short-term and long-term results in the regression analysis. The results indicate that in the beginning, the greater (lesser) the number of direct ties, the lesser (greater) is the knowledge diversity, and over time, this knowledge diversity increases (decreases).

5.2 Relationship management as a knowledge strategy

A firm can design and manage two structural elements to create its knowledge profile. The following knowledge strategy framework can be considered.

Figure 2: Relationship management as a knowledge strategy



In the long run, if a firm wants to increase its overall knowledge and focus on a specific field at the same time, it could benefit by maintaining evenly distributed ties with other firms and by expanding the number of its direct ties (Figure 2, top left). In the case of high-tech products, in which multiple knowledge fields are applied in a complex manner, such as electric vehicles, this strategy is suitable because it is important to focus on knowledge about a specific field while simultaneously developing related technologies. In the case of a mature industry, such as a gasoline-powered vehicle, a high level of knowledge must be accumulated evenly in various knowledge fields. Therefore, it is beneficial to manage relationships with fewer direct ties at low concentration (Figure 2, bottom left). In the case of a high-tech product, such as a personal mobility device, superiority in a specific technology is necessary. In the case of products that require a relatively low level of technology, it is necessary to maintain numerous direct ties and focus on major partners to manage relationships (Figure 2, top right). Lastly, if a product requires a relatively uniform skill, such as a bike, but do not need a very high level of skill, it is appropriate to manage relationships with fewer direct ties and focus on specific partners (Figure 2, bottom right).

6. DISCUSSION AND CONCLUSION

This study contributes theoretically to the knowledge management field as follows. First, it examined the knowledge performance of firms embedded in an inter-organizational network by considering various factors. In the context of inter-organizational network, knowledge transfer and inter-organizational learning is a recent topic that is expanding (Marchiori & Franco, 2020). Most previous studies of network structure and knowledge performance are empirical studies, because it is very difficult to measure the knowledge performance of a firm, especially the ego network, which is a combination of complex factors (Gulati, 1998). This study overcame the disadvantages of empirical analysis by establishing an agent-based model based on the organizational learning theory and by obtaining and analysing vast amounts of data through simulations using such a model. Second, the complex mechanism concerning knowledge performance was exemplified using a dynamic model that includes network-, relationship-, and firm-level factors that affect knowledge performance. By using an agent-based model suitable for modeling emergent phenomena caused by the interactions among various factors, multiple factors were considered to identify the moderating effect.

The findings of this study provide insightful implications for practitioners. First, the findings provide implications for relationship management. This study helps firms design their own knowledge strategies for their targeted knowledge profiles by expounding on the implications of the number and strength of direct ties that firms can create and maintain. Second, we propose a strategic framework for firms to manage their knowledge profiles by identifying the number of direct ties that can be managed directly, the concentration of tie strength, and their relationship with knowledge performance. A firm has structural features that it can control and network characteristics that it cannot manage. This study helps knowledge managers to establish knowledge strategies by suggesting structural network factors—tie-strength concentration and node degree—that firms can directly manage for knowledge management. Third, this study revealed that the relationship between structural factors and performance can vary depending on the situation, such as the network topology, a firm's capability, and the length of time (Ahuja, 2000; Capaldo, 2007; Duysters & Lokshin, 2011; Rowley et al., 2000). By examining the moderation effect of absorptive capacity and network topology on the knowledge performance of a firm, knowledge managers can understand that the effectiveness of the knowledge strategy may differ depending on the firm's own situation and the structure of the industry.

To conclude, it can be said that a firm's knowledge performance can be a driving force for innovation. Firms produce knowledge internally, but they also absorb it from the outside. Firms are embedded in inter-organizational networks, and they absorb and utilize external knowledge. This study examined the relationship between the structural factors of a firm and knowledge performance by extending the organizational learning model into a network. We examined the relationship between two structural factors—tie-strength concentration and number of direct ties—and the average knowledge level and standard deviation of the knowledge profile. The results indicate that the more concentrated the tie strength, the lower is the average level of a firm's knowledge profile. The number of direct ties influences the standard deviation of the knowledge profile, resulting in a negative (positive) effect in the short (long) term. In the long term, the effect of increasing the KP standard deviation of the node degree is strengthened when the absorptive capacity is large.

This study has the following limitations and future research directions. First, the cost of maintaining and managing a relationship was not considered. As the results of this study suggest, exchanging knowledge with multiple partners inevitably is costly. By conducting a cost–benefit analysis of lowering the concentration of relationships and its utility, it is expected that an effective knowledge development strategy can be established. Second, among the factors that can affect the performance of knowledge, the characteristics of the knowledge being diffused were not considered. There may be differences in the transfer of tacit and explicit knowledge. This study did not include the forms of advanced knowledge that can be delivered only through strong ties. In future research, more sophisticated results can be expected if the type of knowledge transferred is considered.

EXTENDED SUMMARY/IZVLEČEK

Podjetja od svojih poslovnih partnerjev pridobivajo različna znanja, ki služijo kot izhodišče za različne inovacije. Ali bo podjetje pridobljeno znanje učinkovito in uspešno uporabilo je odvisno od števila, moči in neposrednosti povezav med podjetjem in različnimi poslovnimi partnerji. Raziskava temelji na modelu agenta ter teoriji organizacijske krivulje učenja. Slednja dokazuje, da je učinkovitost uporabe znanja v organizaciji možno uravnavati preko strukturnih dejavnikov prej omenjenih povezav med podjetji. Močne medorganizacijske povezave namreč znižujejo učinkovitost uporabe znanja; to pomeni, da se raven znanja v podjetju zmanjša v primeru močnih povezav z določenim podjetjem ter hkrati šibkimi povezavami s preostalimi podjetji. Nadalje, število neposrednih povezav dolgoročno povečuje raznolikost znanja v podjetju. Kumulativni učinek moči in neposrednost povezav na znanje se razlikuje glede na vrsto povezav med podjetji. Pri naključnih povezavah se povprečni učinek zmanjšanja znanja ublaži z visoko sposobnostjo vsrkanja znanja, medtem ko se učinek zmanjšanja okrepi v omrežju brez obsega. Avtorji v prispevku predstavijo strategijo, ki služi kot izhodišče za podjetja pri načrtovanju njihovega trajnostno učinkovitega kopičenja znanja.

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