A study on the impacts of informal networks on knowledge diffusion in knowledge management

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Abstract

Knowledge management has garnered attention due to its role of maintaining competitive advantage. Creating and sharing knowledge is an essential part of managing knowledge. However, the best knowledge is underutilized because employees tend to seek knowledge through their informal networks, not reach out to other sources for obtaining the best knowledge. Prior studies on informal networks pointed out a negative influence of heavy reliance on learning through informal networks but they paid little attention to a structure of informal networks and its impacts on diffusion of knowledge.

The aim of our study is to show impacts of informal network on knowledge management by employing a network structure and investigating diffusion of knowledge within it. Our study found out that performance of learning becomes lower in a highly clustered network. Creating random links such as serendipitous learning can improve performance of knowledge management. When employees rely on a knowledge management system, creating random links is not necessary. Costs of adopting knowledge affect performance of knowledge management.

Keyword: Informal network, knowledge diffusion, knowledge management, organizational learning

1. Introduction

Knowledge management has gained a lot of attention because it is regarded as a source for a sustainable competitive advantage. Many practitioners have made various attempts to implement knowledge management but they have witnessed few payoffs from those attempts. Though they implement a knowledge management system of technical superiority, they face a disappointing turnout. Since then, much of prior work on knowledge management has focused on what caused knowledge management to fail and how to improve it.

Studies on knowledge management from the organizational aspect have been conducted. Organizational culture, structure, incentive system and types of knowledge are studies for explaining the failure of technology-oriented knowledge management initiatives [7, 8]. Many suggestions for success of knowledge management are created.

However, employees appear to count more on their peers and colleagues for acquiring knowledge than on a knowledge management system [7, 13]. Informal groups of employees exchange knowledge within their groups, not reaching out to other sources beyond their groups [5]. This does not necessarily lead to selection or adoption of the best knowledge, thereby creating a problem of 'localness' [7]. March and Simon denoted such behaviors as satisficing [15]. They argued that people tend to search knowledge and stop searching when they found knowledge good enough to learn, not the optimal knowledge. Thus, existence of informal networks may inhibit diffusion of the best knowledge within a firm.

Thus, we study how an informal network affects diffusion of knowledge and how we can improve knowledge management in the presence of employees' learning through an informal network. Knowledge diffusion is a dynamic process of sharing through a social network. However, much of prior work on an influence of a social network on knowledge management has not conducted a dynamic analysis of knowledge diffusion in a network. Therefore, we resorted to a computer simulation for analyzing a dynamic process of diffusion and incorporated a graph theory to construct a network structure. In particular, we adopted a β-graph model to build up a variety of a network structure, which ranges from a highly clustered network to a random network [19].

In the next section, we will review prior studies on knowledge management. Next, we will explain the model of knowledge diffusion. We will show the simulation results and provide implications and limitations. Finally, we will give conclusion of our study.

2. Literature Review

Several studies argued that social networks affect knowledge creation and sharing in organizations [5, 13, 17, 18]. Suzulanski emphasized an absorptive capacity of knowledge recipient [17]. Cross and Nohria [5] noted that informal networks are important in knowledge-intensive sectors, where people turn to personal channels for finding information. They pointed out that people rely heavily on their networks even though they can access a stock of knowledge through an IT system. Linden et al. [13] also indicated that employees are likely to resort to their peers than to impersonal sources for knowledge, thereby making a knowledge management system underutilized. Thus, an informal network can be regarded as an essential channel for seeking knowledge.

Some studies focused on negative impacts of learning through informal networks [7, 15]. Davenport and Prusak [7] pointed out that employees seek knowledge in organizational neighbors more often than out in the company with taking efforts and uncertainty of discovering better knowledge. They attributed this tendency to the characteristics of knowledge market. In knowledge market, trust is essential for trading knowledge. However, in general, people trust what they know. Thus, employees depend more on their neighbors for knowledge. As a result, the best knowledge can be underutilized and localized. From the perspective of knowledge market, they call this market failure. Simon and March [15] argued that turning to neighbors and settling for knowledge good enough for themselves is human tendency. They call it 'satisficing'. Thus, learning through informal networks may cause diffusion of knowledge to fail, thereby underutilizing the best knowledge.

Some studies attempted to focus on an influence of a structure of an informal network on information diffusion [9, 10]. Granovetter [9] studies a role of weak ties as a channel for getting information. Strong ties improve speed of sharing information within a network but it experience redundancies of information. Weak ties work as a bridge between a network of strong ties and it can be an important channel for exchanging information. He showed an importance of weak ties by conducting a survey of successful job applicants, about where they can helpful information. Through weak ties, they get more help for getting jobs. His study suggested an influence of a network structure but it does not take a dynamic analysis of knowledge diffusion.

Watts [19] provided a β-graph framework where he showed a small-world phenomenon. A β-graph can construct a variety of networks of which structures range from a highly clustered network to a random network with the change of a parameter β. Much of prior work on a network structure is restricted to a small-sized network but a β-graph model enabled scholars to analyze a large network by using a computer power. Besides, it can also create a various arbitrary network structure by varying randomness of a network. Thus, we can use this for analyzing informal networks, with various types and sizes. However, it emphasized a structure of a network but paid little attention to the characteristics of a node, an employee.

March [16] studied organizational learning by resorting to a computer simulation. As a result, he can take a dynamic analysis of knowledge diffusion and put more emphasis on a learning behavior of an organization and its employees. He focused on learning between an organization and its employees. However, his study is restricted to knowledge exchange between an organization and its employees, thereby ignoring learning between employees.

Therefore, our study takes a dynamic approach of March [16]. To overcome a limitation of his study, we allow learning between employees through their informal networks by incorporating a β-graph, which will enable us to study a variety of informal network structures. Next, we will explain our model.

3. Model

We employed an organizational learning model in March's study [16]. March studied organizational learning and individual learning. He incorporated a method of genetic algorithm to model learning between an organization and its members. Knowledge, a product of learning, is defined as a genetic code that consists of various genes with different values. The superiority of knowledge is determined by its fitness with an environment, a market reality in his study. A market reality is also defined as a genetic code, of which value describes market environment. In certain knowledge, the number of its genes, of which value is equal to that of a market reality, determines its level of fitness with a market environment. As a result, superior knowledge is determined by how many genes match those of a market reality. Learning between an organization and its members creates a variety of knowledge. Among them, knowledge with more fitness with an environment can survive.

March's model [16] has a few limitations in describing organizational learning. First, knowledge may not flow freely between an organization and its members and, as a result, learning may happen as much as its study assumes. Various factors that affect knowledge transfer have been studied on prior works. Costs of knowledge transfer differ depending on types of knowledge. Explicit knowledge should be codified for being transferred. Therefore, codification costs may inhibit smooth flowing of knowledge [7]. Tacit knowledge can hardly be codified and is not easily disseminated within an organization. It can be conveyed effectively through personal contact. An absorptive capacity of a knowledge receiver can affect an effective knowledge transfer [4]. Organizational culture also has an influence on sharing knowledge [7, 8]. Culture must be nurtured for supporting an individual's knowledge-sharing behavior. Proper incentives should be guaranteed to encourage sharing knowledge [7, 8]. Much of prior work on knowledge management ignored that knowledge is not a free product but a valuable one. Therefore, those who share knowledge should be compensated for it.

Second, it also gave little attention to learning between organizational members. Interaction between an organization and its members is the way of improving their level of knowledge. However, knowledge transfer between members should be considered. Knowledge management system supports knowledge transfers between members to create a knowledge map within a firm. Yellow pages are one of ways to guide people to locate which knowledge they need in an organization [7]. In this respect, knowledge management system plays a role of a knowledge broker in a firm. People also rely on their informal networks to find knowledge they need [5, 7, 13, 14]. Even when there is much better knowledge within a firm, people tend to resort to searching and finding knowledge good enough to meet their needs. This is called 'satisficing' [15]. This is attributed to the fact that people decide to adopt knowledge easily found within their informal networks, due to the costs associated with finding out the best knowledge within a firm. In this respect, we assumed that an individual tend to search knowledge within his network and reaching out to others within a firm is costly enough to confine their attention to his network. We incorporated a network structure to study knowledge diffusion within one's local network.

Knowledge

There are three types of knowledge in our model as March's study. One is a reality code that reflects a current market situation. The second one is a firm's knowledge, which is created by knowledge management activity such as evaluating and storing its employees' knowledge. The last one is employees' knowledge. All knowledge is assumed to have m dimensions, which have values of -1, 0, or 1. The value of zero at one dimension represents no knowledge. Knowledge of a firm and its members is evaluated by a reality code. Like March's study, the performance of knowledge is determined by how similar knowledge is to a market reality. Comparing dimensions of knowledge with those of a market reality code, we can count the number of matching dimensions. Counts of dimensions equivalent to a reality code are the performance of knowledge.

Initially, a market reality code is set to have dimensions of which value are -1 or 1. The values at dimensions of a reality code are randomly given by drawing a number from a uniform distribution ranging from 0 to 1. When a drawn number is lower than 0.5, -1 is set to be at one dimension and vice versa. A reality code does not have zero at its dimension because it reflects a market perfectly. A firm is assumed to have no knowledge. Its employees have knowledge, of which dimension is set to have the value of -1, 0, or 1. This reflects that they sometimes have no knowledge at some dimensions.

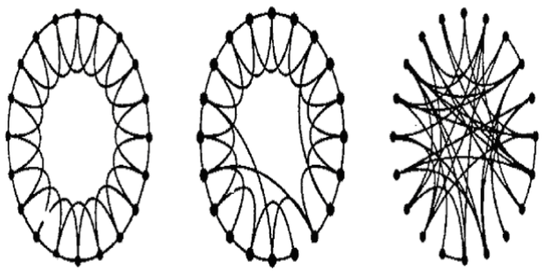
The best knowledge is the one that have all dimensions matching dimensions of a reality code. The worst knowledge is the one that have no dimensions matching a reality code's dimensions.

Network Structure

Our model incorporated a network structure to study knowledge diffusion within a firm's informal network. Much of prior work on a firm's network on knowledge management has focused on a particular topology of a network. We incorporated a small-world graph model suggested by Watts [19] to study knowledge diffusion in informal networks of a firm.

A small-world graph is a tool for creating a variety of network structure, ranging from highly dense network and random network, by adjusting a parameter β. The value of β determines randomness of a network. The following figure describes structures of small-world graphs with varying value of β.

Figure 1. Small-World Graphs



β=0 ⟶ β = 1

Increasing Randomness

A small-world graph has three parameters. One is the size of a network, the number of nodes, denoted *n*. Each node represents one member. Second one is the number of neighbors that one node can have, denoted *k*. One node's neighbors are other nodes connected with it. In graph theory, a connection between two nodes is a link. Each link is defined as relationship between two nodes. Each link represents not only relationship but also information channel between two nodes. In our study, each link does not have direction because two nodes linked with each other can give or take knowledge. The value of *k* represents the number of links one node currently has. The last parameter is β, which determines a structure of a network. At β=0, a network is highly clustered that each node has higher possibility of sharing the same neighbors with other nodes. In other words, densely knit networks emerged. Its structure affects shortest path length between nodes. Though tightly linked, nodes are far away between them that shorted path length becomes longer than other values of β. As the value of β increases and then the proportion of random connection in a network becomes larger, the degree of clustering becomes lower and the length of path between nodes get shorter. At β = 1, the distance between nodes get shorter because nodes are randomly linked and random links create many shortcuts between nodes. However, the degree of clustering becomes lower due to the increase in the number of random connection.

In our study, we conduct a simulation analysis at various values of β, thereby examining impacts of network structures on knowledge diffusion. Davenport and Prusak [7] pointed out 'localness' in knowledge diffusion. The reason of the problem is that people tend to rely on their informal networks due to 'satisficing' behavior [15]. We investigate this by varying the value of β, which determines the degree of clustering in a network structure.

An employee's learning

We assumed that a member go through two stages of learning. At first, he decides to learn from his neighboring members. The way of learning follows March's model [16]. The only difference is that a member learns from his neighbors in the presence of a network structure. He searches better knowledge within his neighbors than his knowledge and make a list of that. Among that list, he attempts to find a dominant value at a particular dimension by counting how frequent a specific value shows up. After finding out dominant values at all dimensions, new knowledge is obtained by applying the adoption rule in March's study. During this process, a parameter affecting learning is a learning rate, denoted as p_e.

March's study [16] gave little attention to selective learning of an employee. For example, if new knowledge is worse than current one, it should be disregarded. However, March's study does not consider this. We assumed that after learning through an informal network, an employee evaluates new knowledge with respect to a market reality code. After that, he realizes how much improvement will be made by adopting new knowledge. Then, he measures the costs of adopting new knowledge by comparing its dimension with the same dimension of current knowledge. Levitt and March [12] noted that better alternatives are not adopted though they are superior to current procedures. This is attributed to the fact that experience accumulated with current procedure keep people from adopting it. They argued that the tendency of sticking to the status quo is likely to be unstable if the differences in potential between existing procedures and new ones are enormous. We assumed that what inhibits adopting new knowledge is difference between old and new knowledge and considered it as costs of adopting new knowledge. Therefore, benefits of old and new knowledge should be large enough to offset these costs if an employee adopt new knowledge.

Counts of different dimensions determine costs of adopting a new knowledge. Total costs are defined as multiplication of the cost of learning through an informal network c_n and counts of different dimensions. More similar dimensions new knowledge lowers costs associated with adopting it. Then, a member compares the performance of current knowledge with the net benefits of adopting new knowledge from the benefits of adopting improved new knowledge and the costs of adopting discrepant one. A member adopts new knowledge when the net benefits are larger than those of current knowledge.

An employee also learns from a firm's knowledge. Generally, he searches, retrieves and learns knowledge from a firm's knowledge repository that organizes and stores knowledge within an entire organization. First, he retrieves and learns knowledge from a repository. He learns each dimension of a firm's knowledge stochastically. His learning rate p_e determines the proportion of dimensions that he learns. New knowledge is created and then is evaluated with respect to a market reality. As a result, the benefits of new knowledge from are determined and the adoption costs are measured by how different new knowledge is from current one. The adoption costs are measured by multiplying counts of different dimensions with the cost of learning knowledge from a repository c_o. As in the case of learning through an informal network, an employee decides to take new knowledge by comparing the benefits of holding on to current knowledge or migrating to new one.

An organization's learning

A firm attempts to assess knowledge of its employees and store the best one. It searches and stores employees' knowledge of which performance is better than that of its current one. Like a model in March's study [16], it finds out the dominant values at all dimensions and learns new knowledge following the rule in March's model. Learning is affected by a learning rate of an organization, p_o. New knowledge will be evaluated and if its performance is better than that of current knowledge, it will be adopted by a firm.

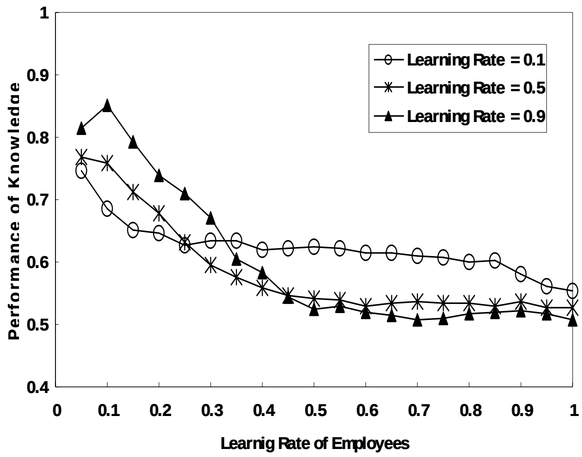
4. Results

First, we conducted simulation experiments of March model in the parameter settings of our model to examine how relaxed assumptions in our model affect learning in an organization. As mentioned before, there are no frictions between knowledge sharing in March's study [16]. Besides, learning between an organization and employees happens. Simulation process follows the way of March's model [16].

We plot average performance of knowledge of an organization and employees along y-axis, which is obtained from 100 simulation runs. The degree of performance of learning is measured by the ratio of matching dimensions with a market reality code relative to total number of dimensions. Parameters are provided in Appendix. For each simulation, average performance of all members including an organization is measured. The plotted value is obtained from averaging results of 100 simulation runs. We plot performance of knowledge diffusion at various values of learning rate of an organization, particularly in the parameters used in March's study.

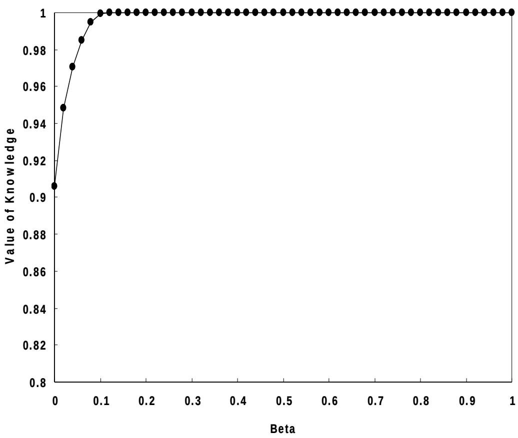
The result shows the same pattern as March's study. We found that slow learning rate of an organization and faster learning rate of employees exhibits the best performance of learning. As an employee's learning rate increases, performance of learning decreases. This is attributed to the fact that fast learning of employees inhibits improving knowledge because employees learn good knowledge fast and as a result, can hardly find better knowledge.

Figure 2. Results of March's model in our model parameters



Second, we conduct a simulation of examining an impact of a network structure on knowledge diffusion. In particular, we focused on whether learning through an informal network creates the problem of 'localness'. We plot average performance of learning along y-axis from 100 simulation runs. The value of various βs is plotted along x-axis. We incorporated costs of learning knowledge through an informal network, denoted as c_n. In this figure, we assumed that there are no costs associated with learning through an informal network. Besides, in this case, we focused particularly on learning through an informal network, thereby excluding learning through a firm's knowledge repository.

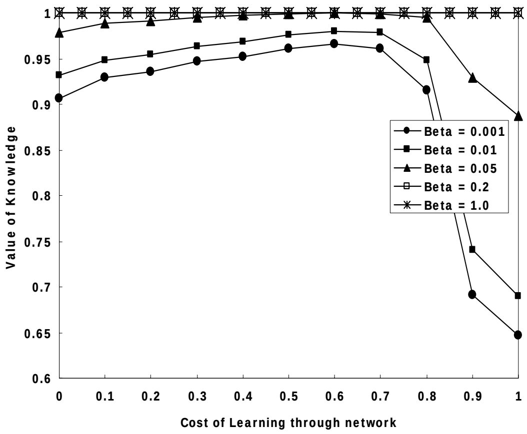
Figure 3. Results of knowledge diffusion through a network



We found that performance of learning is affected by a network structure and it becomes better as the value of β grows. At low β, performance of learning is lower than at other higher β. As we mentioned before, highly clustered network is made at low β. Low performance of learning at low beta means that learning through an informal network, particularly, of highly clustering, cause inefficient diffusion of knowledge. We can conclude that there is a problem of 'localness' as Davenport and Prusak [7].

We conduct an analysis of impacts of varying level of costs associated with learning through an informal network. We plot different values of c_n along x-axis, which ranges from 0.0 to 1.0 and examine performance of learning with respect to several βs. At higher values of β, costs do not have an influence on performance. However, learning costs matter in the range of small βs. At β=0.001, performance decreases sharply around c_n = 0.8 though it reaches the maximum regardless of the size of c_n in the range of large βs. We can conclude that costs should be small enough to improve learning particularly in the firm of highly clustered employee network.

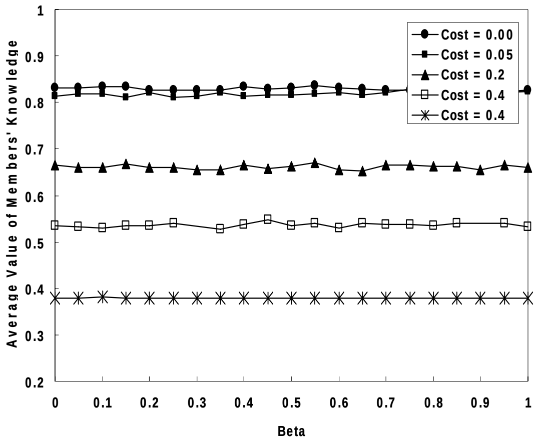
Figure 4. Results of changing learning costs (c_n) at different βs



So far, we examine learning performance in case of no employee's learning from a firm's knowledge repository. We conducted simulation experiments of incorporating two types of learning. First, we confined an employee's learning to learning from a knowledge repository. We examine performance of learning with respect to changing values of c_o, costs associated with learning from a knowledge repository. Performance of learning is plotted along y-axis.

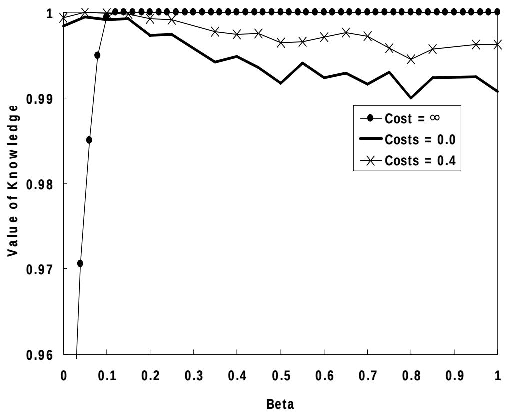
We found out that learning performance depends on the level of learning costs. As costs grow, performance also decreases. However, a network structure does not influence performance of learning because learning through an informal network cannot happen.

Figure 5. Performance with changing β at different learning costs (c_n)



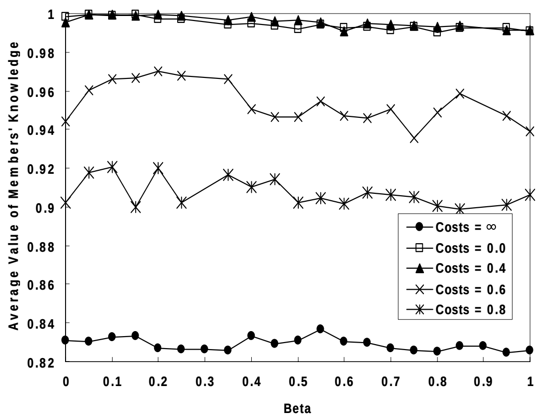
We investigate how performance of learning is affected by a network structure under the presence of friction that is caused by learning costs. First, we look at performance change with varying costs of learning knowledge from a repository but without costs associated with learning through an informal network. As a result, learning through a network is frictionless but learning from a knowledge repository is costly. At $c_o = 0$, no costs incur in learning knowledge. In this case, performance decreases with the increase of β. As c_o grows, performance of learning increase regardless of the size of β. At $c_o = \infty$, where learning from a knowledge repository does not happen, performance of learning becomes large at higher value of β, while performance becomes large at lower values of β in case of learning from a knowledge repository ($c_o \neq 0$). Therefore, no learning through a knowledge repository can inhibit improvement of learning particularly in the case of a highly clustered network.

Figure 6. Performance with changing β at different learning costs c_o (fixed at c_n= 0.0)



We examine performance of learning when learning from a knowledge repository can be done with no costs but learning through an informal network is costly. At $c_n = \infty$, there is no learning through a network but learning from a repository can be done. Performance of learning there is lower than at any other values of c_n. As c_n becomes lower, performance also increases. At less than $c_n = 0.6$, performance decreases with the growth of β. However, at higher values of c_n, it is not certain that performance is affected by β. Thus, when employees resort more to learning knowledge from a repository, a network does not have much influence on performance of learning.

Figure 7. Performance with changing β at different learning costs c_n (fixed c_o at = 0.0)



5. Implications and Limitations

We showed that a problem of localness in a firm can happen as Davenport and Prusk [7] using a β-graph [19]. Varying the value of β, we construct a variety of a network structure, which ranges from a highly clustered one to a random one. In a highly clustered network with a low value of β, where an employee shares the same neighbors with others, learning through a network performs lower than in a random network. We showed this in Figure 3. As a network has more random links that creates shortcuts to others within a network, performance of learning through a network works better.

Thus, a firm should emphasize creating random links within an organizational network, particularly when employees rely primarily on seeking knowledge through their own networks. Many organizations, which tried knowledge management initiatives, encouraged employees to participate in meetings and forums, thereby creating shortcuts to reach out to others with better knowledge by making many shortcuts. Davenport and Prusak [7] called this type of learning, serendipitous learning. This is important when employees tend to seek good enough knowledge within their local networks, not reaching out to others in a firm with the best knowledge [15].

Besides, costs of learning should be considered in implementing knowledge management. Particularly, in a highly clustered network, costs of learning affect performance of learning. We showed in Figure 4. At low values of β, as costs of learning increase, performance decreases. These costs can be regarded as switching costs associated with changing knowledge. Many organizations should consider providing a better environment for learning new knowledge and adopting it. For example, a firm should not stop at holding meetings and forums as a way of serendipitous learning but providing more resources such as time and monetary benefits for adapting employees themselves to newly learned knowledge. This is a way of lowering costs of learning.

When employees depend mainly on a knowledge repository for seeking new knowledge, costs of learning should be lowered. In case of learning knowledge from a repository, a network does not affect performance of learning. We showed this in Figure 5. Therefore, providing opportunities of serendipitous learning is not necessary. After learning knowledge from a repository, sufficient resources should be offered to employees to adopt it.

We showed that how a network structure affects performance of learning when two types of learning are done by employees. When there are no costs incurred in learning through a network, a clustered network improves learning at lower costs of c_o. We showed this in Figure 6. When costs of two types of learning are low, there is no need of creating random links for improving learning. However, when employees count on learning through a network because of high costs of learning knowledge from a repository, creating random links can lead to developing learning. When there are no costs incurred in learning from a knowledge repository, a network structure has different influence on performance of learning with respect to the size of c_n. We showed this in Figure 7. At small values of c_n, a network structure has an influence on performance as we concluded from Figure 6. As a network becomes more random, performance goes downward. However, when c_n becomes larger, performance shows no definite pattern with the change of β. Thus, a firm faces no great need of managing a network when costs of learning through a network become greater.

Our study did not model dynamic change of a network structure. In a firm's network, a variety of changes occur. First, new links are added to a network. Through formal or informal meeting, a number of links increase. Network growth is not considered in our study. This is particularly important for a firm to implement serendipitous learning because it creates random links to a current network. Second, a network loses some links. Turnovers happen in every workplace. This causes a network to lose a node and its links with others. Turnover has been studied because a firm loses an essential knowledge asset after an employee with a stock of knowledge leave [3]. Much of prior work on job turnover has given little attention to a study of turnover from the perspective of a network structure.

Environmental changes have not been addressed in our study. Knowledge management has been introduced to maintain a sustainable competitive advantage under changing environment. In March's study [16], an environmental change has been addressed by changing some of dimensions. Our future study employs an environmental change.

6. Conclusions

Our study focused on knowledge diffusion in a firm, particularly in the presence of a network structure. Much of prior work on knowledge management and organizational learning emphasized a role of a social network on knowledge diffusion [7, 10, 17, 18]. However, it does not conduct an analysis of a network structure rigorously. Our study incorporates a graph theory to study a variety of a network and its influence on knowledge diffusion.

Besides, we incorporated costs associated with learning to reflect the exchange of knowledge with friction. Prior studies on knowledge management, particularly from the perspective of technical superiority of a knowledge management system, gave little attention to knowledge market friction caused by various organizational and economic factors. In our study, costs of two types of learning affect knowledge diffusion and the degree of their influence changes with respect to a network structure. In a highly clustered network, performance of learning can be lower than in other types of network. Costs of learning should be lowered to improve learning in a clustered network.

Appendix

A. Parameter Settings

Parameters	Value
Number of Employees	1000
Number of Dimensions	10
Seed	11111
Simulation Runs	100
Learning Rate for an Employee	0.1
Learning Rate for an Organization	0.9
Learning Costs (c_n) for each dimension	[0.0, 1.0]
Learning Costs (c_o) for each dimension	[0.0, 1.0]
Beta (β)	[0.0, 1.0]

B. Simulation Procedures

1. (time = 0) Create a genetic code that reflects a perfect market situation. It consists of *m* genes. In our study, we denote them as knowledge dimensions. A code of a current market situation is made by setting values to its dimensions randomly. Its values take –1 or 1. Create an organizational knowledge that is created from members' knowledge. It also consists of *m* dimensions. Initially, they are set to be zero. Create *n* number of organizational members of which knowledge consists of *m* dimensions. The value of each dimension is set to be –1, 0, and 1 randomly. The value of 0 at certain dimension represents no knowledge. The knowledge that members have is evaluated according to a code of a current market situation. A member is given a rate of learning new knowledge *p*, a cost of learning from knowledge of his neighboring members, c_n and a cost of learning an organizational knowledge, c_o.

   Create a network of organizational members, using a beta-graph model. The size of the network is equal to the number of members, *n* and a number of neighbors for each member is k. Depending on a parameter, beta, in this graph model, a different network structure is made. The algorithm of a beta-graph model is provided in Appendix. All members have their own neighbors according to a network structure made by beta-graph model.

2. (time = 1) First, all members search and find superior knowledge within their neighboring members. For each dimension among superior knowledge, a member identifies a dominant value that shows up more often than the other values. A member updates his own knowledge for each dimension according to March's organizational learning model. Then, new knowledge is evaluated with respect to a code of a market situation. A cost of learning new knowledge is determined by comparing a previous knowledge dimension with a new knowledge dimension. The number of dimensions where new knowledge differs from previous knowledge is multiplied by a cost of learning knowledge through networks, c_n. Then compare the value of new knowledge, the cost of learning it, and the value of previous knowledge. If the net value of learning new knowledge is greater than the value of previous knowledge, then new knowledge is adopted. This process is conducted for all members.

   Then, all members check if an organizational knowledge is valuable than their own knowledge. If an organizational knowledge is better than their knowledge, he decides to adopt this or not. First, a member updates his knowledge with an organizational knowledge. For each knowledge dimension, a probability of a member's knowledge adapting to an organizational knowledge is determined as a learning rate of a member. A random number is drawn from a uniform distribution ranging from 0 to 1. If this number is lower than a learning rate, a new knowledge will be adopted. Then the cost of learning this new knowledge is measured by calculating a number of different knowledge dimensions in a current knowledge and an organizational knowledge. In this case, the cost is calculated by multiplying a cost of learning an organizational knowledge c_o and a number of different knowledge dimensions. Second, compare the net benefits of incorporating an organizational knowledge with benefits from current knowledge. If the net benefits are higher, a member adopts this.

   Then, an organization starts learning from its members. It searches all members' knowledge and finds knowledge with better performance than its own knowledge. Among better knowledge, it finds out a dominant value at each dimension. It measures how frequent a specific value shows up at one dimension and the value that appears more often becomes a dominant value there. Whether this dominant value is adopted or not is determined by a learning rate of an organization. The detailed method follows March's study [16]. After organizational learning, its knowledge is evaluated.

3. (Stopping conditions) Before learning, the performance of an organization and its members' knowledge is recorded. After learning, if there is no improvement in any knowledge, simulation stops.

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