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How Structural Changes in Complex Networks Impact Organizational Learning Performance

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Abstract: The power of using knowledge against competitors is a key success factor in the information age. However, the knowledge itself is not the source of competitive advantage for an organization; rather its power lies in its use. In a learning organization, collective knowledge of the individuals is needed, in order to reach the overall goals of the organization. From an organizational perspective, the most important aspect of knowledge management is knowledge transfer. Therefore, knowledge within the organization should be available to others through social interactions. The contributions of this paper are two-fold: First, we show that the network structure that emerges from those social interactions depends on the variability in individual patterns of behavior. Second, we emphasize the importance of network structure changes for organizational learning. A consequence is that a high clustering coefficient within a network does not necessarily produce a high learning outcome. It can even result in a loss of innovation. Another consequence is that a small average shortest path length within a network of individuals positively affects organizational learning. Therefore, certain topological features of a network can help network members to have a better access to information within an organization.

Keywords: Complex Networks, Organizational Learning, Knowledge Management, Network Formation.

JEL Classification Numbers: C02, C6, C15, D23, D81, D85, L22, L25, M12, O31.

1. Introduction

Nowadays, the knowledge has become a principal source of competitive advantage, similar to other valuable resources and strategic assets in an organization. Its power lies in its use. The power of using knowledge against the competitors is a key success factor in the information age [1]. However, without proper management of such a valuable resource, utilization of knowledge becomes difficult and ineffective.

Knowledge management is the set of processes that governs the creation, storage, dissemination, and use of knowledge. Knowledge creation, in turn, involves adding new knowledge to existing implicit and explicit knowledge of an organization [2]. Created knowledge can be considered as an essential raw material for innovation and further knowledge creation [5], both of which are leading to new products and services. In today's rapidly changing environment, organizations are forced to create knowledge, in order to avoid the obsolescence of existing knowledge and be successful in the innovation process [3]. While new knowledge is developed by individuals and institutional networks of people, organizations play the key role in the management and flow of such new information. Personal knowledge, however, cannot be considered as organizational knowledge. Organizational knowledge must be captured and shared by members of the organization. Therefore, in order to become an organization with extensive knowledge, mechanisms should be used to store the knowledge for future use [4]. Those steps in knowledge management are called knowledge storage [5]. Distribution and transfer of knowledge is also another important part in the knowledge management process. Obtained knowledge within an organization should be generalized and be available to others through social interactions. The goal of knowledge use is to activate the relevant knowledge, in order to create value for the organization. The activated and relevant organizational knowledge becomes embedded in new products, services, and processes.

In a learning organization, the person-to-person interactions between individuals form a social network of people. It can be understood as an environment, in which learning occurs during the interactions of individuals. Assuming that the resulting social network is a product of its people’s interactions, the first question that comes to mind is how the network structure looks like and what kinds of interactions take place within the network.

In our previous work [6], we proposed a model of network growth, in which the structure of social networks can be inferred by the variability in individual patterns of behavior. We categorized the dynamic processes involved in the evolution of a complex network into two groups: (1) The process, which occurs during the growth of a network with respect to nodes, represents the tendency of new users to establish links to other members upon entry into the network; (2) The process, which occurs among existing users of a network, in order to establish links between them. We also showed that the process, which occurs among existing users of a network when establishing links, is further divided into two categories: (a) The first category includes the establishment of links of a Friend-Of-A-Friend type (FOAF type) with a social distance equal to 1; (b) The second category includes the establishment of random links with other users, who are present in the network. We showed that variability in individual patterns of behavior in social environments lead to a change in the structural properties of the network [6].

A lot of research has been done to determine critical success factors of knowledge management implementations. However, this paper contends that these critical success factors do not pay sufficient attention to the social networks of people. There is a meaningful social network, through which people communicate with one another. Through this interpersonal learning in an organization, knowledge exploitation mainly happens. In order to understand how such networks affect organizational learning, we need to clarify the following research questions: how are the networks formed and what characteristics of the networks affect positively or negatively organizational learning?

For our analysis, we focus especially on the structural properties of complex networks and the obtained payoff of individuals. To the best of our knowledge, existing research of network structures has not investigated the effect of network structures on organizational learning and knowledge management so far.

To answer our research questions, we develop an agent-based model to simulate the collective learning of workforces within an organization. With this model, the organizational learning performance under different structural properties (i.e., the clustering coefficient and the average shortest path length) of social networks is captured and compared with one another. The clustering coefficient and the average shortest path length are measured as a function of time. We also use our model for creating a network that realistically reflects the social interaction among the workforce of an organization

The remainder of this paper is organized as follows: In section 2, we discuss related works and the theoretical background. In section 3, we detail the model and its parameters. Experimental setup and results are presented in section 4 and section 5, respectively. Finally, we present our conclusion and discuss the future work in section 6.

2. Theoretical Background

Successful implementation of knowledge management requires a flexible structure, which facilitates and speed up collective learning. Having a flexible social structure is an important element in the organizational structure in the sense that it provides team members with a chance for knowledge exchange with other team members who have the same interest or similar knowledge. Moreover, it can be considered as a strategy for improving organizational learning performance.

2.1. Organizational Learning

With the development of science and technology, the business environment has become a challenging and competitive one. In such an environment, it is natural to see changes in the context of competition. The greatest competitive advantage in this new business environment is learning. Hence, the only way for an organization to overcome the uncertainty, complexity, and dynamics in the business environment is to have a competent and efficient workforce. The workforce is considered to be an important asset of an organization and the foundation of wealth. Thus, organizations are more successful, if they learn faster than their competitors. That is why more and more organizations employ learning as a competitive advantage.

According to organizational learning theory, an organization is considered to be an adaptive system, which is able to sense changes from the environment and evolve to produce the desired outcome. Therefore, a learning organization actively creates, stores, transfers, and uses the knowledge for its adaptation to the changing environment. The topic of organizational learning was introduced around 1970 in Senge's most popular book “The Fifth Discipline” [7], which describes his vision of systems thinking and learning organizations. In the literature, we can find various proposals for models that facilitate organizational learning [8, 9, 10, 11, 12]. One of those models is the one of March [12]. March's model, which we follow in this paper, captures the development and diffusion of organizational knowledge as a consequence of individuals' socialization.

2.2. Network Topology

There are different networks in the real world, such as biological networks, social networks, and technological networks. Regardless of the way of representing the relationships among their constituents, a network property (e.g., degree distribution) describes an entire network. According to this property, networks can be classified into being similar or different to each other. Network formation mechanism based on degree distributions can be attributed to different network growth models. As an example, empirical data on web and social networks show power law degree distributions. The preferential attachment growth model introduced by Barabási and Albert [13-15] is capable of generating such power law degree distributions. In that model, new nodes are more willing to link to high degree nodes during the growth of a network. The high degree nodes can be imagined to be nodes with better social skills than the other nodes [16]. For example, individuals having more activities in a network would be even more likely to establish relationships with other people with similar social character or social position.

As the resulting social network of individuals within an organization is a product of its constituents’ interactions, the structural analysis of such a network is possible. It is an indicator of various roles, the hierarchy of these roles, and the distribution of power and authority within an organization. Therefore, during the structural analysis, we encounter the network structure and the location of people within it. Based on this, we observe collective learning, which can be internal as well as external to an organization. The learning is a combination of exploration and exploitation of knowledge.

2.3. Exploration and Exploitation

The interest in the classic problem of trade-off between exploration and exploitation in organizational learning grew in the 1990s, reflecting the importance and impact of this balancing act in organization decision making [17, 18]. Similar to recent researches in this area [19, 20, 21, 22, 23, 24, 25, 26, 27, 28], Fang et al. point to the problem of trade-off between exploration and exploitation in organizational learning [21]. According to their model, individuals have the choice either to explore the environment by themselves for achieving the organizational goal or to take part in social activities (which can be regarded as exploitation). The detailed research question, which they investigated in their model, is: “Does a semi-isolated subgroup structure improve the balance of exploration and exploitation, leading to superior long-term learning performance outcomes?" Their research results showed that a modest amount of cross-group linking is associated with a high performance level in learning.

With the help of our proposed simulation model and by following the same basic experimental setup as described in Fang et al. [21], in this paper, we investigate the learning performance for three types of connectivity structures among the individuals of an organization.

3. Model

The situation that we want to model is described with the following scenario: Distribution and transfer of knowledge is an important part in the knowledge management process. Obtained knowledge within the organization should be available to others through social interactions. As the workforce of an organization is capable of obtaining new knowledge according to their own capabilities, joining a network provides them with an additional opportunity for an information exchange with their direct contacts. During such interactions, knowledge exchange happens and new knowledge is created by the individuals. We model an organization as a complex system with different rates of variability in individual patterns of behavior, where learning occurs during the interactions of individuals that are located in it. An organization's learning performance is measured as the average performance across all individuals in the organization.

3.1. Entities

Similar to March's model in organizational learning [12, 21], our model has three main entities: an external reality, individuals, and an organization. The external reality is the organizational goal, which is described with a binary vector having m dimensions. The binary vector has values of 1 or −1. Values are randomly assigned with the probability of 0.5. Furthermore, there are n individuals in the organization. Each of them holds m beliefs about the corresponding elements of reality at each time step. Each belief for an individual has a value of 1, 0, or −1. A value of 0 means an individual is not sure of whether 1 or −1 represents the reality. As mentioned earlier, our model is different from Fang et al. in that an organization is seen as a complex system, wherein individuals interact with each other according to different network structures. In Fang et al. [21], a fully connected network structure is considered.

3.2. Structural Properties of Networks

A key factor for understanding the dynamics of our model is the topology of interaction patterns among individuals. The topology of interaction patterns can be described through the properties of the network structure. Therefore, different underlying network structures allow us to test how a network structure can contribute in the learning performance of the system.

In this paper, we analyze two of the main structural properties of a network, namely the average shortest path length, AVL, and the clustering coefficient, CC. The shortest path length is defined as the shortest distance between node pairs in a network [29]. Therefore, the average shortest path length, AVL, is defined as shown in the following equation:

$$AVL = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i<j} l_{ij} \tag{1}$$

where N is the number of nodes within the network, and l_{ij} is the shortest-path length between node i and node j.

The clustering coefficient of a node i, C_i, is given by the ratio of existing links between its neighbors to the maximum possible number of such connections [29]. Thus, the clustering coefficient, C_i, is defined as:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{2}$$

where E_i is the number of links between the neighbors of node i, and k_i is the node degree of node i (i.e., the number of links connected to node i). Averaging C_i over all nodes of a network yields the clustering coefficient of the network, CC. It provides a measure of how well the neighbors of all nodes within the network are interconnected locally.

4. Simulation Environment

The experimental settings for our model are as follows: We conduct multi-agent-based simulations in Netlogo to test our model [30]. An advantage of agent-based simulation is that, from a computational perspective, it allows parallel execution by having a separate computational thread for each agent (node) that is responsible for the information exchange. Another advantage is that it allows dynamically changing the computing environment to model the real scenario.

4.1. Experimental Setup

To check the performance of learning organization while individuals exchange information, simulation runs are conducted. Each simulation run lasts 100 time intervals. Each simulation result that is reported in Figure 1C has been averaged across 10 simulation runs.

The number of individuals in each organization is set to n = 250. The number of dimensions in the beliefs is set to m = 100. The reality is determined by randomly assigning a value of 1 or −1 for each of the 100 dimensions, whereas each dimension of an individual's belief set is determined by assigning a value that is uniformly drawn from 1, 0, or −1. In general, each organization consists of c clusters of individuals. In this study, the number of clusters is set to c = 1 (Table 1)

4.2 Social Network Creation Model

Similar to our previous study [6], we generated a network that shows the connectivity pattern among the individuals within an organization. The generation of the network is based on three parameters: P_{GM}, P_{FOAF}, and P_{RAN}. They represent the rate of adding new nodes with one new link, the rate of establishing links of FOAF type, and the rate of establishing links of random type, respectively. The value of P_{GM} determines the rate of network growth. For example, if P_{GM} = 0.25, it indicates that 25% of the network growth comes from a new link connecting a newly entered individual to the network. 75% of the network growth comes from individuals creating links among themselves.

Table 1. Values of simulation parameters.

Simulation Parameters	Remarks	Parameter Values
N	Number of individuals in the organization	250
M	Dimensions of beliefs	100
Z	Size of a subgroup	250
T	Simulation runtime	100
C	Number of clusters	1
S	Degree of complexity	5
$\mathbf{P_{learning}}$	Probability of individual learning from the majority view	0.3

The value of P_{RAN} is the complement to P_{FOAF} ($P_{RAN} = 1 - P_{FOAF}$). Thus, if the value of the P_{FOAF} parameter equals 1, no random link formation exists in the model. These parameters have values in the range [0, 1]. They represent the fraction of establishing links of random type or links of FOAF type. For example, if $P_{FOAF} = 0.5$, it signifies that the probability of converting a link with social distance of 2 to a link with social distance of 1 is 50%. The remaining 50% probability is used for link creation of ransom type. This network formation approach enables us to simulate and profoundly comprehend the dynamic transformations of a network and its effects on the structural properties of the network.

4.3 Payoff Function

Similar to the Fang et al. model [21], the learning probability of individuals in our model is set to 0.3 (Table 1). Our learning model is adopted from the generalized learning model of March [21]. The payoff function is presented in equation 3:

$$\phi(x) = s\left(\prod_{j=1}^{s} \delta_j + \prod_{j=s+1}^{2s} \delta_j + \cdots + \prod_{j=Ls+1}^{m} \delta_j\right). \tag{3}$$

where x_j denotes j-th element of the bit string x. If $\delta_j = 1$, x_j corresponds with reality on that dimension; Otherwise, it does not. The parameter s, which is $1 \leq s \leq m$, serves as a tunable parameter that can control the difficulty of the search problems. In fact, we have a m-bit string, which is partitioned into L independent subsets. Within each subset, there are s bits that are coupled. Larger values for parameter s make the search problem more interdependent and increase the complexity of the problem. As we can see, the payoff of each individual is calculated by comparing each bit of his/her belief set with bits of the reality set. Therefore, if s = m, all bits must be matched with the reality bits to produce a payoff, making receiving a payoff difficult. In our formulation, we set its value to 5

During the interaction with his direct contacts, each individual identifies those with superior performance than him and, subsequently, makes decisions on updating his belief. The decision to update each of the m dimensions of his belief is made with some probability, $P_{learning}$, reflecting the ability of individuals to learn from one another. The decision rule is based on the idea that the belief sets of the high-performing peers have been closer to reality. When there is no superior performer, the previous beliefs must be intact. If there are two or more superior performers, the new belief will be determined for each of the m dimensions based on the majority of beliefs of the high-performers (i.e., if the majority of high-performers state that the value of a bit is 1 (or -1) then we change our own bit to 1 (or -1), otherwise the bit is set to 0). An organization's performance is measured as the average performance across all individuals in the organization.

5. Results

To investigate how structural changes within the topology of a complex network affect organizational learning, we simulate the organization learning performance of our generated networks and average the results based upon 10 simulation runs. For this, we compute the average payoffs of the population for each time period $t = 0, \ldots, 100$ (Figure 1C). An equilibrium occurs when all individuals have received a similar knowledge level (i.e., payoff). Since the rate, at which people join a network in reality, is much lower than the rate of link creation among existing people, it is safe to assume that most of the existing processes within a social network are related to the establishment of links of FOAF type or random type. It means that the rate of newly entered individuals is much lower than the rate of creation of links among existing individuals. Therefore, we consider the value of P_{GM} to be 0.25, while the value of P_{FOAF} is selected from 0.25, 0.50, and 0.75.

Figure 1A and Figure 1B show the measured CC and AVL of the networks derived from our network formation model. Considering Figure 1A, it can be seen that the CC values constantly decline over time with a decrease in the value of FOAF type links and an increase of random type links. Figure 1B suggests that the AVL values increase consistently over time with a reduction in influence of FOAF-type links and an increase in influence of random links. It must also be noted that the CC values reach their maximum in the early simulation stages due to a small population size, and afterwards, shows oscillation. With respect to the AVL values, the minimums are in the early simulation stages.

Based on the results shown in Figure 1A and Figure 1B, we can check which structural changes within a network can be translated into a positive learning outcome. For measuring the learning performance of the n individuals within our generated networks, we assume that the individuals have the same reality and individual belief sets. Hence, the only thing that differs for them is the network structure. The result of our simulation is shown in Figure 1C.

Our first observation is that the organizational learning performance is different with respect to different connectivity patterns of individuals. Second, as the simulation results show, the information exchange within a network having small amount of FOAF type and large amount of random type links provides to the whole population a better learning performance. This shows that, in such a network, the diversity of belief sets is low. Third, the organization has achieved a high level of correct knowledge about reality compared to other network configurations. Therefore, we can conclude that connectivity patterns among the workforce affect organizational learning.

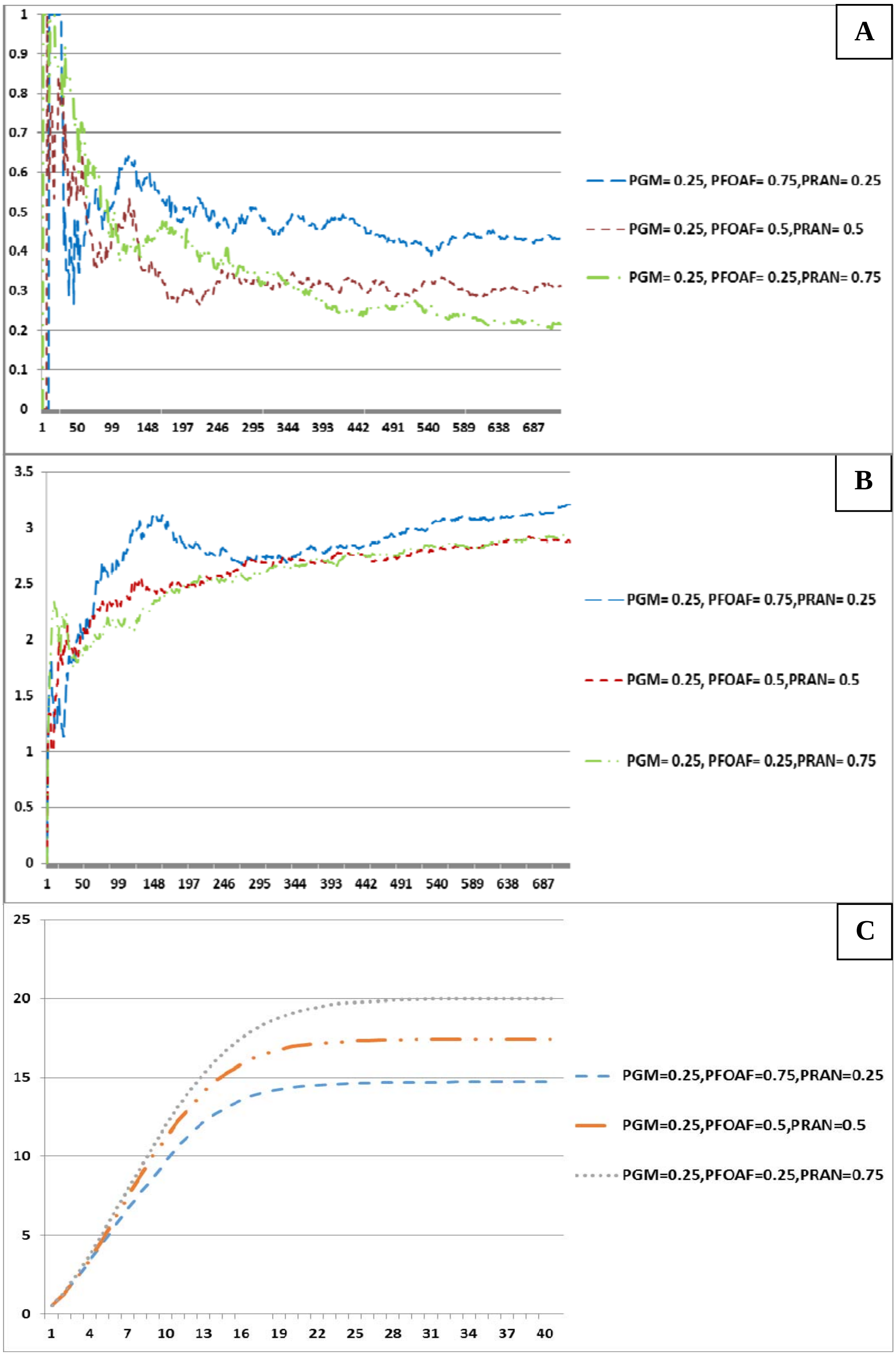

Figure 1. (A) Changes in CC with respect to variability in individual patterns of behavior are shown. The x-axis depicts the simulation period, while the y-axis shows the CC value. (B) Changes in AVL with respect to variability in individual patterns of behavior are shown. The x-axis depicts the simulation period, while the y-axis shows the AVL value. (C) Changes in organizational learning performance with respect to variability in individual patterns of behavior are shown. The x-axis shows the simulation period, while y-axis shows the organizational learning performance (payoff as shown in equation 3).

Comparing Figure 1B and Figure 1C, we can conclude that a network structure with shorter average shortest path lengths can provide a high learning performance for its members. Another conclusion is that a high clustering coefficient within a network does not necessarily produce the highest learning outcome (Figure 1A and Figure 1C). This is quite interesting because it indicates that an increase in the number of FOAF type links stops the innovation in learning. Therefore, with a high number of random type links, the diversity of belief sets becomes small and, as a result, the learning outcome increases. This supports our statement that, in addition to having a realistic model of interactions, a proper network structure is needed to capture organizational learning performance.

Contrary to the result reported by Fang et al. [21], our results (Figure 1C) indicate a low organizational learning performance. Although an explanation could be related to the fact that we model the organization as a single cluster, we conjecture that: (1) Fang et al. assumed a fully connected network among the members of the clusters; (2) There is an overlap among the beliefs of each group, which has not been discussed in [21]. Therefore, the high complexity of knowledge in our model (i.e., a large value of m) causes a low proportion of correct beliefs. Consequently, we conclude that the larger the amount of information is, the longer it takes to learn correct knowledge.

6. Discussion and Conclusion

Social network analysis has the potential to tell us what the interesting features of networks are from both theoretical and practical perspectives. There have been considerable amounts of social network research with the focus on capturing the characteristics of certain networks. However, the extent, to which such varieties of structural properties affect the outcome of individuals' interactions, has received little attention. Therefore, we argue that the current trend of network structure analysis should be shifted, so that the results obtained from the analyses can be used as an indicator for forming optimal network structures. This paper provides a framework to compare how the combination of payoff schemes and network structure changes within a complex social network can determine the best learning outcome.

We believe that the social relationships between individuals in an organization can be utilized to produce positive returns. Despite the creation of new knowledge and the process of learning at an individual level, organizational structure affects the nature of human interactions and information flow. We argue that structural changes within a network of people in an organization affect organizational learning. Therefore, we investigate the role of such structural changes within an organizational structure as a mechanism for increasing the knowledge flow and organizational learning.

The results of our analysis indicate the fact that structural changes within the topology of the network affect organizational learning. The learning performance consistently increases with a decrease in the rate of FOAF type links and an increase of random type links among the population. Therefore, we concluded that higher clustering coefficient within a network does not necessarily produce the highest learning outcome and even stops innovation in learning. Instead, shorter average shortest path lengths within a network of individuals positively affect organizational learning. Our experimental results also show that the existence of links of random type within a network facilitate and increase learning among the population. Consequently, we can state that certain topological features of a network can help network members to get better access to information exchange processes within an organization.

As an extension to our current work, we are interested to test the learning performance of an organization with a few clusters within which varieties of connectivity patterns are observable. We are also interested to see how overlapping and non-overlapping beliefs affect the organizational learning performance.

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