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Individuals' Power and the Learning and Innovation in Multi-stakeholder Societies on Collaborative Platforms Powered by Digital Social Media

Chathura Prasanna Rajapakse, Takao Terano
Tokyo Institute of Technology 4259, Nagatsuta, Midori-ku, Yokohama, Japan
(E-mail: chathura@trn., terano@dis.titech.ac.jp)

Abstract: In social groups, some individuals have a better say than the others. Thus, when it comes to sharing new ideas and making decisions, their voice is better heard over the others. This can be considered as a situation, where power dynamics are applied in social learning. With the advancements of social media, organizations and the knowledge management community have started thinking of creating platforms to co-create value by getting the involvement of multiple stakeholders for learning and innovation. Such platforms results larger societies of stakeholders with divergent interests, where power dynamics are more likely to occur. Given that the influence of power is not adequately researched in social and organizational learning domains, in this paper, we present an agent-based computational model of a learning organization to evaluate the impact of individuals' informal power on learning outcomes.
Key words: Power; Organizational learning; Social innovation; Social media; Social learning

1 Introduction

Advancements in social media technologies have opened up new ways for organizations to learn and innovate. As some researchers have pointed out some years ago, one way of increasing innovation capacity is by widening the framework of participation to a wider community[8]. Furthermore, as some recent research point out, to foster innovation, organizations need to develop places, which they call platforms for collaboration, for different stakeholders to come and work creatively [16]. There are some interesting discussions going on in online forums about the potential of social media to foster innovation by shifting all or part of the innovation process from R & D department to a larger crowd, which comprise of employees, experts, customers, etc. According to those discussions, social media enables the communication and processing of innovative ideas of a wider community.

But most organizations and processes are inherently complex entities, which comprise of multiple interdependent components and a change in one component is more likely to occur unexpected changes in many other components. Consequently, interests of the stakeholders who represent those components are more likely to have conflicts with each other. Therefore, idea sharing is not a smooth process as it is commonly perceived in most organizational learning theories. An idea conceived in an individual's mind has to be accepted by the others in order to be shared and become 'organizational' for implementation. One important factor in this context, which has been largely ignored though, is individuals' power to influence others[2], [4].

In any social group, there are some individuals who have a better say than the others. One's say in a given social group reflects how positively he or she is perceived in that society. Such positive perceptions enable them to make the others to behave in ways that they would otherwise not behave. This ability can be considered as informal power of individuals rather than formal positional power. As the digital platforms for collaboration powered by social media enables larger societies of stakeholders with divergent interests, learning in such societies can also be influenced by such power dynamics. In this research, we are mainly interested in the likelihood of informal power dynamics that exists in societies to occur in digital societies and their impacts on the learning outcome of the organization.

Taking the Agent-based modeling approach, which Robert Axelrod calls the third way of doing science, we propose a computational model of a learning organization, in which socially connected member agents of a complex organization actively participate in enhancing organizational performance, having individuals' 'Say' as the basis of corporation. This paper is to introduce our proposed model and discuss its potential to serve our purpose. The rest of the paper is organized as follows. In section 2, we discuss the related work and in section 3, we explain the proposed model. Section 4 and 5 provides the discussion and future work respectively

2 Related Work

2.1 Multi-stakeholder participatory learning, social media and individuals' power

There is a vast body of research in organizational learning processes, most of which having the commonality "learn (individually), share and store". It means that learning occurs in individuals, they share what they learned among each other and finally the shared learning gets stored in organizational routines and procedures. A comprehensive review on this topic can be found in [2]. Having its roots in organizational learning models of Argyris, Senge, Wenger, etc, [7] has introduced a social learning model to explain how learning takes place in social communities. According to their model, for social learning to take place, three conditions have to be met. 1. It should demonstrate that a change in understanding has taken place in the individuals involved. 2. It should demonstrate that this change goes beyond the individual and becomes situated in wider social units. 3. It should occur through social interactions and processes between actors within a social network.

However, as many researchers point out, sharing is not taking place so easily. According to [4], organizations are inherently political arenas and consequently, so are the processes of organizational learning. The ideas and opinions of individuals resulting from their learning have to be accepted by others in order to be implemented at the organizational level. As discussed in [4], which ideas get accepted largely depends on which actors in organizations are most able to influence organizational decision making. A similar idea is presented in [2], where they address the issue of power in relation to organizational learning in the context of Corporate Environmental Management. They discuss the process of corporation among multiple stakeholders with divergent and conflicting interests. Sharing the view of influence as an equivalent to power, they state that influence occurs when a stakeholder makes another actor behave in ways that he or she would not otherwise do.

A similar idea to what we call 'Say' here can be found in [3], which they name as 'People Sensemaking'. According to them, 'People Sensemaking' is the process a person goes through to get a general understanding of 'Who someone is'. In[6], the same authors use a case study of an internal social network of a large enterprise to explain how it helps to maintain effective ties among its members in terms of communication and sharing. Taking the same case study, in [3] they show how 'People Sensemaking' occur in such a socially connected environment.

2.2 Computational modeling of complex organizations

According to [10], computational models of complex systems such as teams, task forces and organizations can be used to reason about the behavior of those systems under diverse conditions. Also known as computer simulation, it involves representing a model as a computer program. Complex systems, as stated in [11], by their very nature resist analysis by decomposition. Alternatively, to take a computational modeling approach means not having to assign an objective to an organization and instead modeling the agents that comprise it with explicit attention to how decisions are made and how the interaction of these decisions produces organizational output [5]. It enables to work with a vast parameter space and avoid issues arising from non-linear relationships, which are very common in natural processes.

As a technique for computational modeling of complex organizations, the use of NK model has been discussed in [5] and [12]. Even though it has its origin in the Biology field, NK model has been introduced to the organizational modeling field by Dan Levinthal in 1997 [12]. In this perspective, the primary task of the organization is to constantly search for and adopt routines that improve (not necessarily maximize) its performance. The NK Model has two main parts namely, the NK Landscape and the agents that continuously search the landscape. This is seen as typically taking the form of managers of various departments independently searching for better routines[5]. The two main parameters of the NK Model, N and K, represent the number of functions (or components) that comprise the organization (N) and the number of dependency relationships that each function (or component) has (K). In the original NK Model, each function could take two values, either ON or OFF and the search space was made based on each combination of such ON/OFF values. But there is a vast body of research that uses the NK Model with many variations from the original model[12]. Each function and the associated dependencies create the individual payoffs of each function. The overall payoff of the organization then becomes the mean of individual payoffs.

Many organizational models that uses NK model have been introduced in[5] while more specific discussion on application of NK Model for organizational strategy has been presented in [12]. In addition, a model that uses the NK Model to analyze organizational deviation and KAIZEN activities has been explained in [13].

3 The Proposed Model

As shown in Figure 1, the proposed model represents a complex organization, which comprise of a group of member agents who are connected by a social network. We assume here that this social network bypasses any hierarchical boundaries in the organizational structure. Agents individually learn new ideas to improve the organizational performance and share their ideas with other members through the social network. The ideas that are accepted by many other members get qualified to be implemented and become organizational knowledge. Once a new learning is implemented, the associated payoff is granted to the member agents with a feedback, which in turn affect their future behavior.

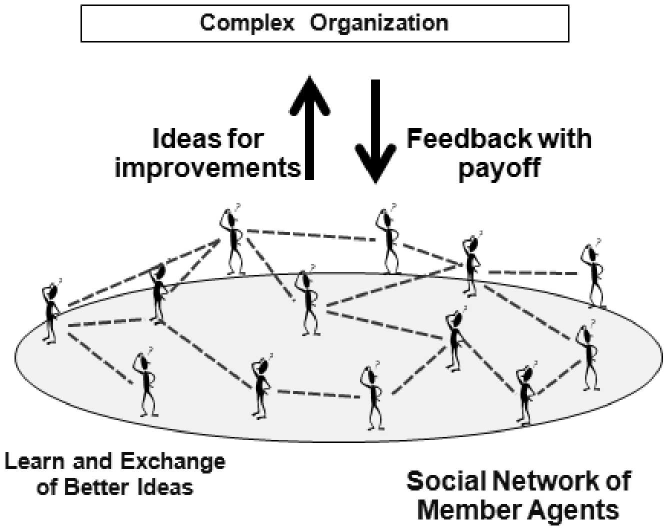

Figure 1 Overview of the Proposed Model

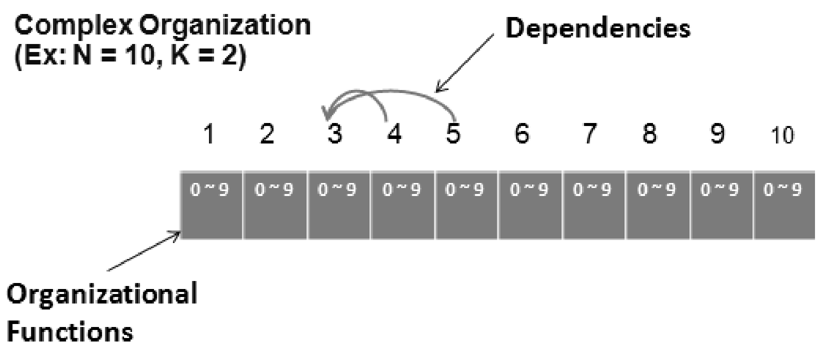

Figure 2 Representation of the complexity of the organization

As shown in Figure 2, the complex organization in our model is represented with N number of functions (or components), and K number of dependency relationships with other functions. Selection of the K number of other functions has two options. One is to select the next K number of functions of each function as the functions, upon which the particular function depends. For example, as shown in Figure 2, function 3 depends on function 4 and 5 as K is set to 2. Similarly, function 10 depends on function 1 and 2. The other option is to randomly select K number of functions instead of selecting the K number of adjacent functions. In our model, these two options are controlled by a parameter. Apart from that, each function can be at D number of states, which is also a parameter in our model. Each state is represented as an integer value ranging from 0 to (D-1). For example, if D is set to 10, each function can be at state 0 to 9 as shown in Figure 2.

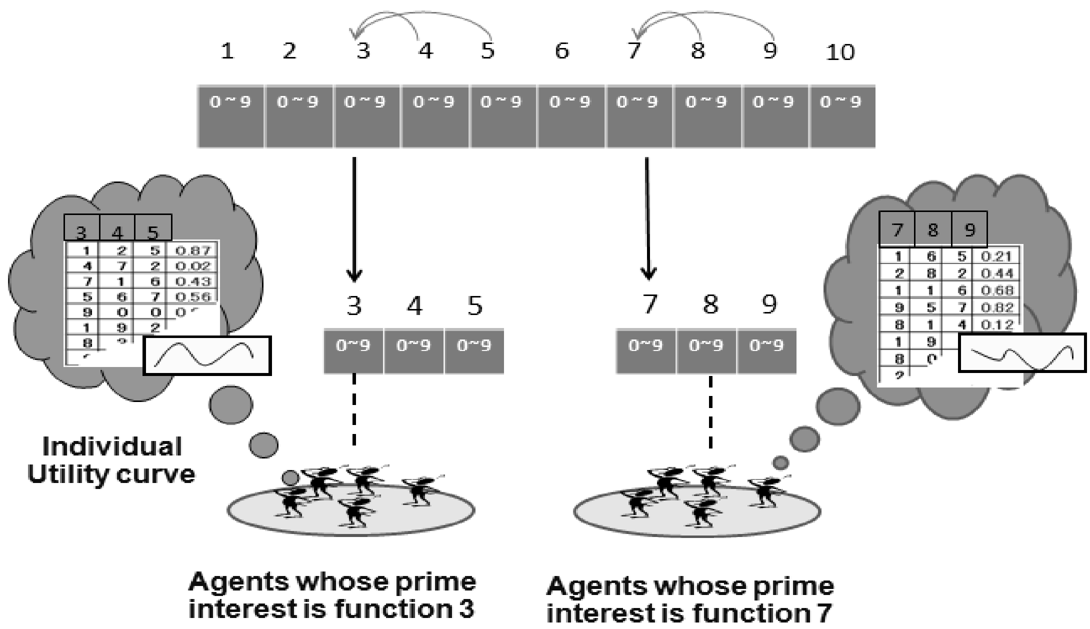

Figure 3 NK Model based lndividual and Organizational Utility Landscapes

3.1 Modeling the search space

Each function in the complex organization comprise of a random amount of agents who hold that particular function as their prime interest. Since each function depends on K number of other functions, each agent in the system gets a search landscape of (K+1) dimensions. For example, agents in Figure 3 have a 3 dimensional individual search spaces as K = 2 in the given organization. Given that there are D number of possible states for each function, each individual search landscape has $D^{(K+1)}$ possible value combinations. The payoff value corresponding to each value combination is selected randomly.

This results in unique individual utility functions for each agent in the system, which makes idea sharing conflicting. The organizational utility for a given value combination then becomes the average of all individual utilities (payoffs) for the particular value combination. As the payoff values are selected randomly and K can range from 0 to N, the individual utility landscapes become complex and rugged. Individual learning takes place when the individual agents continuously search for improvements in such utility landscapes. Taking an evolutionary approach, we use a real-coded genetic algorithm (RCGA) [14] to represent individuals' learning.

3.2 Modeling agents' decision rules

As each agent has a unique individual utility function, new learning always result in different payoffs for different agents. As shown in Figure 4, new learning of *agent A*, when compared to individual utility functions of A and B, results in a higher payoff for *agent A* but a very poor payoff for *agent B*. Therefore, in an ideal situation, B would have rejected the new idea of A. But the same new idea, if implemented at the organizational level, has the potential to give reasonably good payoffs for both A and B. Due to this uncertainty, agents in our model do not take decisions to accept or reject new learning by merely evaluating against their individual utility functions. Instead, they use their perception about the individual who propose the new idea to evaluate the potential outcome.

Here, agents' perceptions about other agents are basically determined by their past experiences and each agent maintains a history of outcomes of new learning of all agents it has interacted so far. For example, *Agent B* in Figure 5 has a history of learning outcomes of *Agent A*. According to the table in Figure 5, a given new learning of A can be 'G' (good) or 'B' (bad) when evaluated against B's individual utility function. The same new learning could have given 'Good' or 'Bad' payoffs to B, if implemented at the organizational level. Otherwise, it could have been 'Failed' to be selected for implementation. Using the table, for example, B can know how many times new learning of A, which was evaluated as good (G) according to his individual utility function, has actually given 'Good' outcomes if implemented at the organizational level.

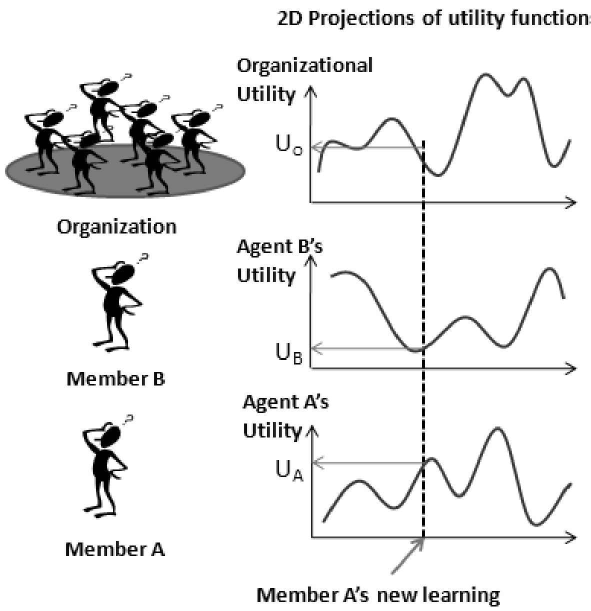

Figure 4 How new learning results in conflicts among agent's interests

Having such a history enables evaluating new learning in terms of the conditional probability of being 'Good' at the organizational level. If *P(Good/G)* denotes the probability of being 'Good' when evaluated as 'G' at the individual level and *P(Good/B)* denotes the probability of being 'Good' when evaluated as 'B' at the individual level, according to the Bayes' Theorem;

$$P(Good/G) = P(G/Good) \times P(Good)$$

$$P(Good/B) = P(B/Good) \times P(Good)$$

The prior probability *P(Good)* denotes the probability of the particular agent's new learning to become 'Good' at the organizational level. Initially, *P(Good) = P(Bad) = P(Fail) = 1/3.*

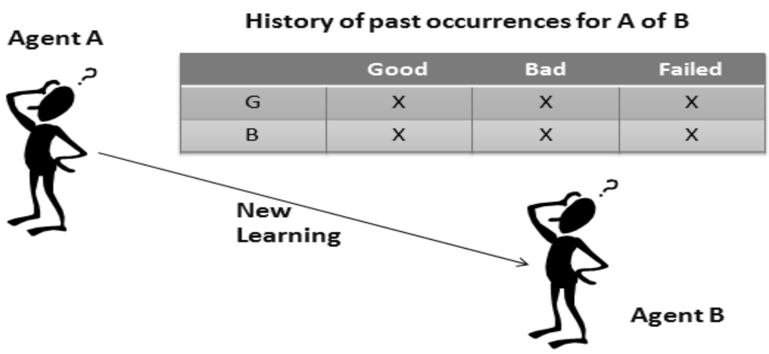

Figure 5 How an agent evaluate new learning of another agent

3.3 Functionality of the model

Our proposed model is driven by individual agents' desire to maximize their payoff by contributing to the improvement of the organizational utility. For that they continuously search in their individual utility landscapes for new and better ideas. Thus at each time period, agents come up with newly learned ideas. However, in a natural setup, not all agents come up with new ideas at an equal rate. To maintain this difference in idea generation, we have introduced a probability variable for each individual, which determines whether that individual learn a new idea or not at a given time period.

Since agents are connected socially by the social network, each agent gets new ideas learned by others from those who are connected to them. Thus, at each time period, each agent has a pool of new ideas to consider both learned by him or herself and by other agents in the society. Agents evaluate their pools of ideas at each time period based on the probability of giving good results as explained before and if they find a better idea than the one they currently hold, they accept it and pass it to the other agents that they are connected with.

The organization, which is also an agent in our model, scans the society of its stakeholder agents at each time period and picks up the mostly spreaded idea for implementation. Once it is implemented, it evaluates the utility to the society and distributes that utility equally to the entire society. Once the agents receive the utility based on the new idea implemented, they evaluate whether it is good or bad to him or her and update the history table of the respective individual who came up with that idea accordingly.

4 Conclusion

The history of learning outcomes that a given agent maintains about him or herself as well as the agents connected to him or her acts as a memory component of that agent. As the agents use that memory to evaluate the likelihood of a new idea to give a better outcome, it can be considered as a process, in which the perception about the owner of the idea plays a key role in getting acceptance to a given idea. Putting another way, the ideas of agents who have a better performing history are more likely to be accepted than that of others. Therefore, we believe that such agents in our model mimics the individuals who have a better say in a social group.

Furthermore, the learning process under this model corresponds with the Social Learning framework of [7]. As the individual agents, at each time period, come up with better ideas through the continuous search in their individual utility landscapes, it can be considered as similar to a change that occurs in individual's understanding (point 1). As the learned new ideas get spread through a social network of members it can be considered as corresponding with point 3. Finally, the fact that mostly spread new ideas get implemented at the organizational level can be considered as getting situated in a wider social unit (i.e. Organization) (point 2). In addition to that, as the social learning framework discussed in [7] is based on ideas of existing organizational learning theories, our model can be considered as contributing to the existing social and organizational learning literature by exploring the impact of individuals' informal power on the learning outcomes.

This model is currently under development using the agent development toolkit of Repast Simphony [15]. As a result, we are lacking with results for further discussion. Once implemented, we expect that it will explore some interesting insights about the phenomena being researched. Besides, we have identified some limitations of the current model, which we expect to rectify in a second version. One is, it may not be natural to assign only one prime interest to a member in an organization. Rectifying this may result in more complex individual utility functions. But in our opinion, this will not make a significant impact to the accuracy of the answer to the main research question apart from contributing to enhance the validity of the model to the natural process. Another limitation is that our social network is a static network generated randomly. This is also not representing the natural process and therefore we expect to make it a dynamic network with agents adding and deleting links with other agents depending on the outcomes of their communication.

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