SIMULATION OF KNOWLEDGE INTERACTION AND KNOWLEDGE CONVERGENCE IN GROUPS

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Abstract- To guide a business organization to creative results, intra-group members must undergo learning where there is mutual sharing of possessed knowledge. Intra-group learning, however, may not necessarily progress as intended. Our study thus uses multi-agent simulation to investigate what kinds of behaviors (movements) by individuals within a group will lead to convergence of overall group knowledge in a positive direction. Our results clarify that the type of communication method (focusing on the sensitivity of positive agent) that promote knowledge convergence varied with the knowledge emergence conditions (occurrence or non-occurrence).

Keywords- Knowledge-Interaction, Knowledge-Convergence, Multi-Agent Simulation, Group Dynamics, Team Learning.

I. INTRODUCTION

A key activity for generating constructive results by a team performing tasks at a business site is the mutual sharing of knowledge (e.g., group targets and information possessed by each team member). Yet, this learning within a team is a strictly neutral concept and does not necessarily lead to progress in desired directions, namely, the creation of new value. For example, even when, changes occur in the task being performed, stored knowledge searched within the group may be outdated and used as is (without change) [1]. Also, leaders and members who have experienced previous success may prefer to maintain the current state and not risk novel exploration [2]. Thus, learning entails these negative aspects that could limit progress in more applicable directions [3, 4].

Nevertheless, research regarding how the activities of individuals with appropriate knowledge can converge, so as ensure that the knowledge of the group is channeled in the correct direction, is limited. Much existing research on team learning has used psychometric statistical analysis to examine causal factors among variables [5]. Thus, there has been insufficient use of time-series analyses, and more effort is needed to study mutual interactions and the related effects of knowledge sharing among team members.

Computer simulations may serve as an effective approach to these problems. Simulations straddle the fields of theory construction and theory verification, and are especially effective in the analysis of "simple theories" (undeveloped theories with few constituent concepts that have experiential and analytical foundations of a reasonable scale and related issues). The simulation approach is especially effective when there are mutually interacting processes and time lags, nonlinear effects, and tradeoff relationships [6].

An example of previous simulation research on organizational learning and team processes elucidates decision-making processes within an actual company. Comparisons were made between model predictions and actual data on the basis of specific concepts such as (1) deriving quasi-resolutions to a problem, (2) rejecting improbabilities, (3) searching for problem-solving orientations, and (4) enabling organizational learning [7]. Researchers have also compared the performance of small-scale teams with large-scale hierarchical organizations [8], using experiential learning and procedural learning of organizational members as variables [9]. Recent studies use multi-agent simulations to investigate project management leadership. The results show that projects requiring innovation benefit from inputs of project managers from multiple knowledge domains [2].

Yet, the field of simulation research still requires more study on the internal processes of organizations. Although a few framework studies address intra-organizational processes, the literature includes only one review by Carley on modeling of intra-organizational processes [9]. Unfortunately, Carley's model is complicated, thus weakening the significance of the results [10]. In other words, previous research has not sufficiently clarified what types of actions (behaviors) of individual team members can guide the knowledge of the group as a whole in an innovative direction.

To address these shortcomings, the present study performs an experimental multi-agent simulation to ascertain the effects of knowledge interaction among team members and to review whether and how it leads to knowledge convergence. We also investigate the approaches agents possessing positive knowledge can take to promote speedier convergence of overall group knowledge in a positive direction.

II. SIMULATION FRAMEWORK

This section first establishes the simulation framework and then explains the configuration of the simulation model.In accordance with the aim of this study, two types of agents—positive and negative—are set in the simulation. Here, "positive" knowledge

refers to innovative knowledge and information concerning current work duties. Conversely, "negative" knowledge denotes old knowledge and information needed to conduct current work duties. Similarly, a positive agent is a team member who is highly oriented toward innovation whileperforming his/her job, while a negative agent is a team member who persists in usingthe current/old methods while performing his/her job. We imagined that each agent would be mutually impacted by the knowledge possessed by his/her neighboring agent. We thus investigate what kinds of actions (behaviors) by (of)a positive agentwould enable convergence of the wholegroup's knowledge toward a positive direction.
We suppose the following four types of behaviors(actions) of positive agents, considering the currentrealities in business.

Type 1-1: Random local movement type
Type 1-2: Random wide-ranging movement type
Type2-1: Environmentally perceptive high-sensitivity movement type
Type 2-2: Environmentally perceptive low-sensitivity movement type

The behavior described in Type 1-1 is that of an agent who moves randomly at a slow pace and interacts with neighboring agents. This behavior signifies an individual who moves in a limited space within his/her given environment (for example, in his/her affiliated section or at his/her desk, etc.) to communicate with peripheral team members.

Type 1-2 refers to an agent who performs random movements over a wide area and interacts with neighboring agents. Compared with Type 1-1, this type is not restricted to exchangeswithin a limitedarea but is able to communicate randomly with a variety of members.

Type 2-1 denotes an agent who moves on the basis of information from peripheral agents; if the peripheral knowledge is not highly positive, then this type of agent tends to move. He/she determines how peripheral members perceive their jobs, and if their orientation toward innovationis high, then this agent will stay at that particular site. Conversely, if peripheral members have lowinnovative orientation, then this type of agent will move. That is, this agent is a team member who considershis/her interactions with the periphery, and if another agent possibly increaseshis/her innovative orientation, then the Type 2-1 agent will align himself/herself with that agentand maintain a distance from other agentswith lower innovative orientation.

Type 2-2 perceivesthe knowledge of peripheral agents, and even if their peripheral knowledge is not highly positive, this type will not move.This type is the opposite of Type 2-1, in that such an agent will not move even if the innovationorientation of peripheral members is not high; he/she will remain at that site and continue interacting. That is, like Type 2-1, this agent perceiveshis/her interactions with the periphery butwill continue interacting with another agent even if he/she lowershis/her own innovation orientation.

On the basis of the described framework, simulationsare performed to determine which type of agent has the highest probability of causing convergence of overall group knowledge in a positive direction.

III. CREATION OF THE SIMULATION PROGRAM

3.1. Formation of the map and agents

The simulation model was created using Net Logo 5.2.0. First, a map with sides -16 to +16 (*X*- and *Y*-axes) was created. Next,fifty (50) agents possessing two types of knowledge, positive and negative, were created for A and B each respectively. For instance, an agent A had knowledge of +50, while an Agent B had knowledge of -50. Each agent was generated based on a random initialvalue coordinate.

3.2. Knowledge interactions among agents

Each agent obtains information about the knowledge of the neighboring agents at eight (8) sites. For each tick (time inscribed as discrete steps), the said agent absorbs 10% of the mean energy of the agents at the 8 neighboring sites (hereafter, "knowledge amount") and changeshis/her own knowledge amount. When the knowledge amount of an Agent A declines to below zero (0), it generates an Agent B possessing a knowledge of 0, and Agent A is eliminated. Similarly, when the knowledge amount of an Agent B rises to above 0, it generates an Agent A possessing a knowledge of 0, and Agent B is eliminated.

3.3. Agent movements

An Agent A can select two types of movements. The first type of movement is a simple random movement. The second method of movement is based on a standard value vis-à-vis the mean knowledge amount at its periphery (hereafter,"sensitivity"). If the mean knowledge amount of his/her neighboring agents is equal to or above his/her sensitivity, Agent A will remain on his/hercurrent coordinate. If the mean knowledge amount of his/herneighboring agents is less than his/hersensitivity, Agent A will randomly select a direction from 0° to 360° and revolve accordingly. After revolving, Agent A will then jump 20 units in that direction.
For every tick, an Agent B will randomly select a direction from 0° to 360° and revolve accordingly. After revolving, he/she will move in that direction. **Fig. 1** shows an actual screen of this simulation as described above.

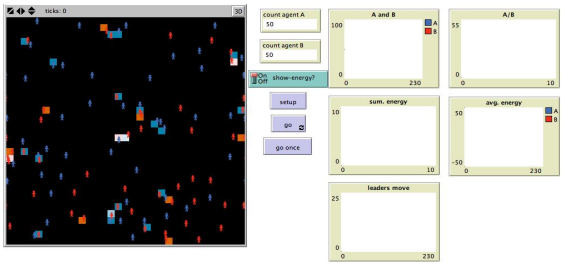


Fig.1. Simulation screen shot

IV. EXPERIMENTAL RESULTS OF MULTI-AGENT SIMULATION

4.1. Comparisons of knowledge convergence depending on Agent A's movement distance

First, to compare the efficacies of Types 1-1 and 1-2, as described in Section 2, simulations were performed by changing Agent A's movement distances. **Table 1** shows the experimental design. This experiment hypothesizes that Agent A has no information about the knowledge of his/herperipheral agents. Thus, there are no selection options for behavior (movement) in response to sensitivity, and the agent moves in a random direction. From Condition 1 through Condition 17, the 1-tick movement distances of Agent A were changed by two units each, from 0 to 32. Simulations were performed 100 times for each condition.

Fig. 2 shows theresults of this experimental design. It compares the percentages of convergence to positive knowledge (convergence rates) for all agents and the number of times to convergence (mean ticks).The results show that the convergence rates trended from 47% to 66%, with no major differences between Condition 2 through Condition 17. However, convergence was slightly high as 75% in Condition 1.

The speed to reach knowledge convergence averaged between a mean of 86 ticks to a mean of 112 ticks respectivelyfor the movement distances of 2 to 32, with no major differences among movement distances. However, for the simulation condition with 0 movement distance, time to knowledge convergence recorded a mean 205 ticks, somewhat longer than the corresponding values for the movement distances of 2 to 32.

Table 1: Experimental design for changes in the movement distances of Agent A

Condition	Agent A		Agent B
	Sensitivity	Movement Distance	Movement Distance
1	0	0	2
2	0	2	2
3	0	4	2
4	0	6	2
5	0	8	2
6	0	10	2
7	0	12	2
8	0	14	2
9	0	16	2
10	0	18	2
11	0	20	2
12	0	22	2
13	0	24	2
14	0	26	2
15	0	28	2
16	0	30	2
17	0	32	2

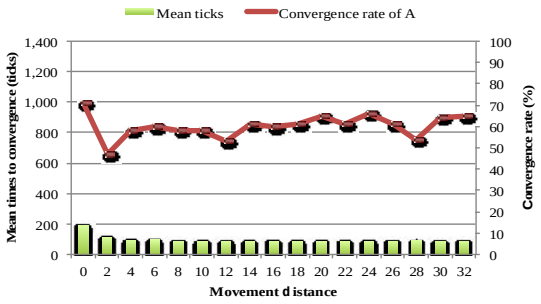


Fig.2. Knowledge convergence comparisons depending on Agent A's movement distances

4.2. Comparisons of knowledge convergence depending on Agent A's sensitivity

Next, to compare the efficacies of Types2-1 and 2-2 as described in Section 2, simulations were performed by changing Agent A'ssensitivities. **Table 2** shows the experimental design. This experiment hypothesizes that Agent A possesses information about the knowledge of his/herperipheral agents. Thus, to enable movement of Agent A when the knowledge amount in his/herperiphery is below a fixed value, the sensitivity setting was set as described in Section 3.3. From Condition 1 through Condition 9, the sensitivity of Agent A was changed by 10 each time. Simulations were performed 100 times for each respective condition.

On the basis of this experimental design, **Fig. 3** shows thecomparison of percentages where all Agents A converged to positive knowledge (convergence rates) and the number of times to convergence (mean ticks).The results indicate a trend; when the sensitivity of an Agent A was low, it was easier for wholegroup knowledge to converge in a positive direction. When the sensitivity of Agent A was +15, there was convergence of knowledge in a positive direction at a probability of 80.0%.However, when the sensitivity was +20 and above, the probability of knowledge convergence in a positive direction was extremely low at 18.0% or less. Conversely, when sensitivity was +10 or less, there was a roughly 100% probability of knowledge convergence in a positive direction.

Time to knowledge convergence ranged from a mean of 195 ticks to a mean of 707 ticks; compared with the condition of random movement shown in Section 4.1, the time to knowledge convergence in this case is longer. When sensitivity was 5 or less, time to knowledge convergence ranged from a mean of 296 ticks to a mean of 645 ticks; yet, when the sensitivity was 10 or above, it took a relatively short time, from a mean of 196 ticks toa mean of226 ticks, for knowledge to converge in a positive direction.

In addition, we observed the process of knowledge convergence. As a result, process has been confirmed that (1) the number of agent A was reduced, (2)

Agent A assembled in several places, (3) Agent B was closer to this small groups and (4) Agent B was weeded out.

Table 2: Experimental design for changes in the sensitivities of Agent A

Condition	Sensitivity	Agent A Movement Distance		Agent B Movement Distance
		Above Sensitivity	Below Sensitivity	
1	-50	0	20	2
2	-45	0	20	2
3	-40	0	20	2
4	-35	0	20	2
5	-30	0	20	2
6	-25	0	20	2
7	-20	0	20	2
8	-15	0	20	2
9	-10	0	20	2
10	-5	0	20	2
11	0	0	20	2
12	5	0	20	2
13	10	0	20	2
14	15	0	20	2
15	20	0	20	2
16	25	0	20	2
17	30	0	20	2
18	35	0	20	2
19	40	0	20	2
20	45	0	20	2
21	50	0	20	2

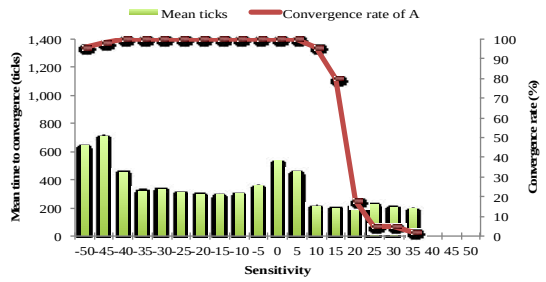


Fig.3. Knowledge convergence comparisons depending on Agent A's sensitivity (NOT considering knowledge emergence)

4.3. Comparisons of knowledge convergence considering Agent A's emerging property

Finally, simulations were performed considering the knowledge emergence of Agent A. This experiment hypothesizes that Agent A learn a lot more when they interact with more innovative agent. We changed the knowledge-absorbing rate of Agent A.When the mean knowledge amount of peripheral agents is equal to or above his/her own knowledge amount, Agent A absorbs 40% of the knowledge amount of peripheral agents andchanges his/her ownknowledge amount. If the mean the mean knowledge amount of his/her neighboring agents is less than his/her own energy, Agent A absorbs 10% of the mean knowledge amount of his/her neighboring agents and changes his/her own knowledge amount as in the previous experimentin Section 4.1.We did not change the other settings at all. Based on this settings, simulations were performed by changing Agent A's sensitivities.

Fig. 4 shows the results of this experiment. We compared convergence ratesand mean ticks.The results indicate a trend; when the sensitivity of an Agent A was close to 0, it was easier for whole group knowledge to converge in a negative direction. When the sensitivity of Agent A was +10 and above, the probability of knowledge convergence in a positive direction was extremely high at 94.0% and above. In addition, when the sensitivity of Agent A was -20 or less, the probability ofknowledge convergencein a positive direction was slightly higher at 64.0% and above.However, when the sensitivity was 0, the probability of knowledge convergence in a positive direction was extremely low at 11.0%.

When sensitivity was -10 or less, Time to knowledge convergence ranged from a mean of 506 ticks to a mean of 781ticks. When sensitivity was 5 and above, time to knowledge convergence ranged from a mean of 132 ticks to a mean of 206 ticks; compared with the condition shown in Section 4.2, the time to knowledge convergence in this case is shorter.

In addition, we observed the process of knowledge convergence. When the sensitivity of Agent A was low, the same process was observed as Chapter 4.2. Conversely, when the sensitivity of Agent A was high, process has been confirmed that (1) the number of A and B were balancedtemporarily, (2) Agent A did not assemble and they were disperse, and (3) the number of Agent A sharply increased.

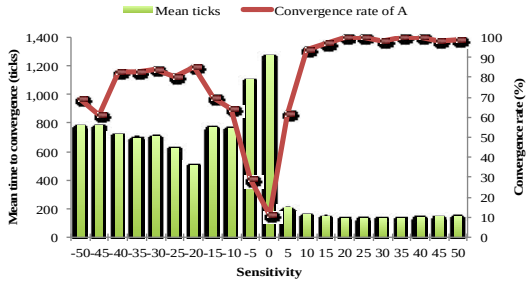


Fig. 4. Knowledge convergence comparisons depending on Agent A's sensitivity(considering knowledge emergence)

DISCUSSION AND CONCLUSION

5.1. Efficacy of methods for raising wholegroup innovativeness

The results of the experimental results described in Section 4 are considered from the perspective of the analysis framework described in Section 2. First, almost no differences in knowledge convergence rates were caused by movement distances of Agent A. That is, so long as there are identical numbers of agents, whether knowledge will converge in a positive or negative direction is determined largely randomly, regardless of movement distance. It can thus be said that neither Type 1-1, performing communications only with limited movements, nor Type 1-2, communicating over broad ranges (as described in Section 2) has high efficacy in terms of directing (impacting) the innovativeness of the entire group.

Second, excluding knowledge emergence from consideration, when the sensitivity of Agent A is

above a fixed value, then there is a low possibility of knowledge convergence in a positive direction. That is, the results suggest that possession of information about the knowledge of peripheral members is not necessarily linked to wholegroup innovativeness—rather, it may possibly have negative impacts. Thus, a Type 2-1 agent, who, on the basis of the information he/she possesses regarding peripheral knowledge, interacts only with members who have a highly innovative orientation, may pose higher risks of reducing group innovativeness than members who have no information about peripheral knowledge and simply move randomly in the context of Agent A is not respected.

Conversely, when the sensitivity of Agent A lies below a fixed value, then there is a high possibility of knowledge convergence in a positive direction. That is, a Type 2-2 agent, whose information and knowledge may be negatively impacted by a member who has low innovativeness orientation, may—by persistently remaining in one place and working with members having low innovativeness orientation—efficiently guide whole group knowledge in an innovative direction.

Third, if knowledge emergence occurs, when the sensitivity of Agent A is above a fixed, then there is a high possibility of knowledge convergence in a positive direction. That is, in such an emergence situation, a Type 2-1 agent who attemptto search for the innovative members may possibly have positive impact. These results indicate that this type of communication as a free explorationto take advantage of such a situation in which Agent A is respected.

Fourth, the time required for knowledge to converge may differ depending on the sensitivity of Agent A. A Type 2-2 agent, whose innovationorientation is high, may, by working with a member whose innovationorientation is low, have higher knowledge convergence rates, but the time required for knowledge convergence becomes longer. Conversely, if there is aggregation of Type 2-1 members with high innovation orientation, although the knowledge convergence rate may be lower, it takes a shorter time to reach convergence. Similarly, although members with high innovativeorientation, such as Types 1-1 and 1-2 (who do not possess information about peripheral knowledge), do not have high knowledge convergence rates under their stated conditions, the time to knowledge convergence is short.

In light of the above, among the four types of agents established in the analysis framework described in Section 2, it appears that Type 2-2 embodies the ability to positively orientate overall group knowledge with comparatively high probability. It is also thought that communicating only with members like Type 2-1 with a high innovationorientation involves a greater risk of reducing group innovativeness than communicating with Types 1-1 and 1-2 with their random movements. Still, in the situation considering knowledge emergence, Type 2-1 made a success for changing positively with the fastest time and the highest probability. Thus, when considering task performance-related limitations and risks that may result in failure, it is essential to investigate appropriate innovation techniques (methods) suited to ateam's actual status.

5.2. Theoretical implications

The theoretical implication of our study is its clarification of the types of communication among team members that are efficacious in raising the innovativeness of an entire group. Previous research on teamlearning approaches using qualitative questionnaire surveys is based on methods that do not sufficiently consider time-series analyses and mutual interactions among team members when attempting to answer what kind of behaviors (movements) of individuals having the requisite knowledge will enable wholegroup knowledge to converge in a positive direction. Further, simulation research on the theme of intra-organizational processes has been traditionally scant. Our study thus makes anotable contribution to the literature in that it proposes communication methods for raising overall group innovativeness.

5.3.Practical implications

In terms of practical implications,our findings can be applied to actual team-based task implementation. Our results clarify that one particular type of communication can be efficacious when team members with high innovationorientation attempt to lead whole group innovation.

First, we found that to communicate innovative knowledge to the entire group, the aggregation of only high innovationorientation members is counter-productive. Naturally, members with high innovationorientation are indispensable at business sites undertaking humanresource development and organizational development. However, in order to steadily improve the skills and abilities of all group and/or organization members and to lead these groups to creative results, it may be efficacious to form teams with both innovative members and members who do not have such an orientation.

Additionally, to successfully increase the probability of overall worksite innovationorientation in organizations that knowledge emergent is hardly occurred (e.g.,they have a high group pressure), even with members with low innovationorientation in the periphery, it is important to maintain highly innovative members continuously at that site. In practical terms, to achieve a good probability of successful organizational innovation, frequent

changes for innovation-orientated team members in terms of physical seating arrangements, project member selections, and personnel transfers, may not be efficient. That is, even if the individual may suffer short-term negative impacts, continuous interactionsfor such members are essential in achieving long-term innovation at the organizational scale.

Meanwhile, our results suggest the necessity of selecting appropriate methods in accordance with specific time limitations and thesituations of knowledge emergence posed by a certain group or organization. For example, when one wants to improve overall group innovativenesswith members who are very used to groupthink, even if doing so requires a longer time, then one should probably choose memberswho are patient and dedicated to working with other team members having low innovativeness. Conversely, when one wants to raise overall group innovativeness in a short time period, then cultivating the climate that respect innovative members will probably increase the likelihood of overall group innovationorientation within a shorter timeframe.

Thus, our study provides practical implications regarding the kinds of team learning practices that need to be implemented to obtain creative results.

5.4.Future Research

Additional research in simulation studies is required to refine our findings and improve their applicability to real-world situations. The present study focused on knowledge interactions among team members as one means of fostering overall group innovation. We need to incorporate concrete details of other kinds of knowledge interactions, including knowledge overlaps, reflection, diversity, and so on, to heighten the practical implications of our findings at business sites. For example, to consider a broader, more diverse spectrum of the knowledge domain,simulations that change the relative ratios of each member type in a time-series analysis are required while modeling knowledge interaction types among group members.Analyses of group morale and previous successes may also be added to the model. This will enable testing of more effective organizational development methods, thus increasing the practical usability of our results.

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