SIMULATION AND EXPERIMENTAL STUDY OF KNOWLEDGE MANAGEMENT IN AN ORGANIZATION

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ABSTRACT

A multi-agent simulation and a gamified computer-aided human experiment is employed to explore how the interactions between individual knowledge workers and the evolutionary knowledge creation (innovation) and diffusion (imitation) affect the organizational performance and the emergent structure under a turbulent environment. Surprising result of a Non-monotonicity in organizational performance has been discovered in the simulation and validated in the gamified experiment. This study further discusses and pinpoints the unique characteristics and advantages of both simulation and gamified experiment. Future research directions are also highlighted.

INTRODUCTION

Knowledge Management (KM) has been formally established in 1991 as a multi-disciplinary field of study (Nonaka, 1991) for achieving organizational objectives by making the best use of knowledge. Many large companies and non-profit organizations have resources dedicated to internal KM efforts (Addicott et al., 2006) since knowledge is the ultimate source of value creation and competitive advantage. This is also the case for nations or regions (Toffler, 1990; Drucker, 1993). KM then has been fuelled by methodologies such as questionnaire survey, observation and interviews, narratives, social network analysis, or data mining. However, difficulties have been found in both theory advancement and industrial applications, especially in coping with complexity and uncertainty. The methodological choices and sophistication hit a bottleneck while the firms' KM enthusiasm and endeavor falls down. Conventional approaches either do not allow describing the complex phenomena from bottom-up generated from the individual interactions or do not have the capacity in handling large scale studies for exhibiting relevant experimental results. Additionally, they still have the deficiency in truly revealing the dynamic knowledge flows since no simple or linear causal relationship can be easily identified. Once thriving, KM is barely striking and flourishing.

The objective of this research is to offer a new methodological alternative through simulation and experiment in managing organizational knowledge, leveraging the bottom-up emerging properties and exploiting how organizational performance is influenced under turbulent and complex environment. In this study, a multi-agent simulation is performed based on a previous model (Chang, 2005) to explain how knowledge workers solve problems and achieve optimized goals with a freedom of choice on either creating new knowledge (innovation) or acquiring shared knowledge (imitation) from others through the social network. The frequencies of these two behaviors depend on agents' past experience incorporating reinforcement learning. The research also explores the evolution of organizational structure and collective performance based on interactions of agents in a complex and dynamic environment. One of the interesting findings indicates that organizational collective performance is not monotonically improved by either promoting innovation or encouraging imitation. The simulation is then validated via a gamified computer-aided human experiment. The application of multi-agent simulation together with human experiment in organizational development and knowledge management suggests a profound, robust and scientific approach on tackling complexity and uncertainty issues involved in the field of study. With the developed multi-agent simulation of knowledge creation and sharing in an organization, further strategic policies can be designed and tested before execution without sacrificing any scarce cost or introducing undesired risks.

MULTI-AGENT SIMULATION

In an organization, individual knowledge workers are making effort to achieve better performance when facing various tasks by a freedom of choice on either innovation or imitation. For innovation, agents create new knowledge to improve the solution; whereas for imitation, agents connect to the social network and acquire shared knowledge. Each individual must choose how to allocate their effort between innovation and imitation. Modeling the social network allows an examination of emerged structure as well as tracking evolving choices between innovation and imitation. Knowledge creation and diffusion occurs in the context of a dynamic and turbulent task environment as represented by stochastic movement in optima. Establishing the simulation model allows us to explore how the innovativeness of individuals and the emerged structure influence the organizational performance.

2.1 Modeling the Agent

2.1.1 Task

In an organization, there are M agents. Each individual $i \in \{1,2,\ldots,M\}$ faces N separate tasks. There are several different methods available for each task. The methods chosen by an agent for a given task is represented by a sequence of d bits, either 0 or 1, thus there are 2^d possible methods available for each task. In any period t, an agent i is fully characterized by $N{\bullet}d$ dimensions. Denoted by $z_i(t) \in \{0,1\}^d$, so that $z_i(t) \equiv (z_i^1(t), \ldots, z_i^N(t))$ and $z_i^h(t) \equiv (z_i^{h,1}(t), \ldots, z_i^{h,d}(t)) \in \{0,1\}^d$ is an agent i's chose method in task $h \in \{1, \ldots, N\}$. An example with N=12 and d=4 is given below:

Task (h)	#1	#2	…	…	#12
Task methods ($\underline{z}_i^h(t)$)	1101	0110	…	…	1011
	ß $\underline{z}_i(t)$ à				

2.1.2 Heterogeneity of Agents

To measure the degree of heterogeneity between two methods vectors, z_i and z_j, "Hamming Distance" is used which is defined as the number of digits for which the corresponding bits differ:

$$D(\underline{z}_i, \underline{z}_j) \equiv \sum_{h=1}^{N} \sum_{k=1}^{d} \left| z_i^{h,k} - z_j^{h,k} \right| \tag{1}$$

2.1.3 Goal and Performance Measurement

Corresponded to each task, there is a goal vector which is also a sequence of d bits. Each agent has different goal vectors which may shift from time to time. Agents have to utilize chances to improve the current method set and get as close to the goal vectors as possible. Therefore, the agents' performance is measured by hamming distance between the method and his/her goal. The shorter the distance the better the performance is. The organizational performance is then measured by an average value of M individuals' performance.

Denote $\hat{\underline{z}}_i(t) \in \{0,1\}^{Nd}$ as the goal vector of agent i in period t, $\hat{\underline{z}}_i(t)$ may be different from period t to period $t+1$ indicating the task environment and goals are dynamically updating from time to time. It may also be different among agents, implying diversity in agents' problems faced.

Each period t, each agent needs to get closer to the goal of selected task. Given N tasks with d bits in each task and the goal vector $\hat{\underline{z}}_i(t)$, at period t, the performance of agent i is measured by $\pi_i(t)$ which is the hamming distance between the goal and agent i's method:

$$\pi_i(t) = N \cdot d - D(\underline{z}_i(t), \hat{\underline{z}}_i(t)) \tag{2}$$

The performance of the organization $\bar{\pi}(t)$ is measured by how close the agents are to their respected goals collectively which is the averaged values in period t.

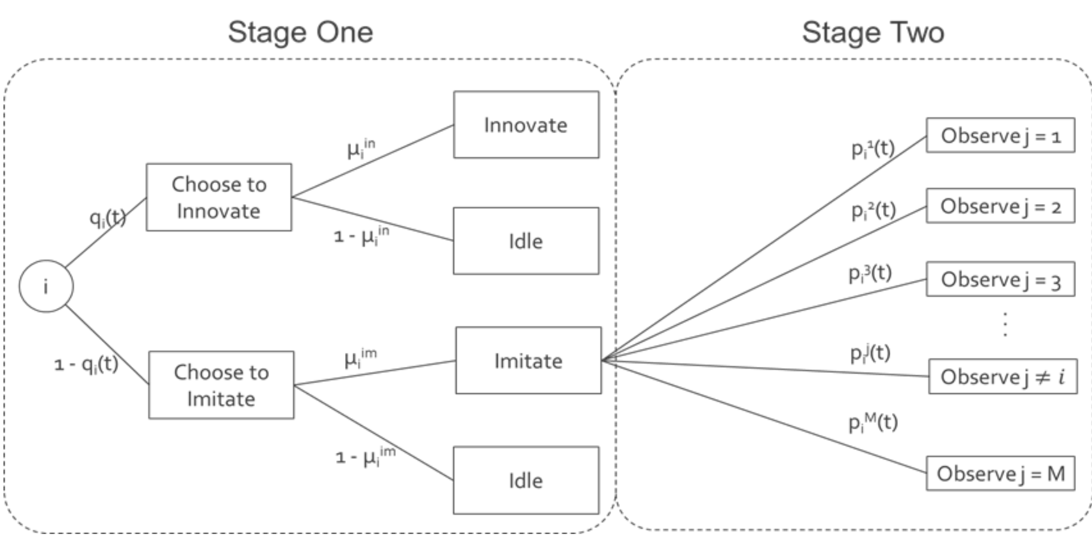
$$\bar{\pi}(t) = \frac{1}{M} \sum_{i=1}^{M} \pi_i(t) \tag{3}$$

2.2 Defining Agents' Learning Process

2.2.1 Innovation and Imitation

Within each period, agents have to decide whether the behavior is innovation or imitation. Agent's knowledge creation and diffusion framework is illustrated in Fig.1. Within each period, agent i will have chance to update his/her method and get closer to the goal and shorten the hamming distance by freedom of choice on either innovate or imitate as shown Fig. 1. Innovation occurs when an agent independently create new knowledge – a random new method for a randomly chosen task. Imitation occurs when an individual connects to the network, selects someone and then acquires his/her method to the randomly chosen task currently deployed by that agent. Within each period t, only one task will be chosen for method improvement.

FIGURE 1
AGENT'S KNOWLEDGE CREATION AND DIFFUSION FRAMEWORK.



Denote μ_i^{in} as the innovation productivity of individuals, and μ_i^{im} as the reliability of the social learning. Under μ_i^{in} probability, agent i can create new knowledge, while under $1-\mu_i^{in}$ probability, agent i fails to create new knowledge or stay idle. Under μ_i^{im} probability, agent i can connect to the network and search for others, while under $1-\mu_i^{im}$ probability agent i fails to connect to the network or stay idle. μ_i^{in} and μ_i^{im} are two exogenously specified and imposed parameters in the model.

2.2.2 Assessment of Innovation and Imitation

Whether the chosen action of either innovation or imitation is considered to be successful also depends on Hamming distance. If the newly created knowledge by innovation or acquired shared knowledge by imitation shortens the Hamming distance between agent's current method and the goal, it is considered successful. Otherwise it is not.

Within each period t, agent i has a current method $\underline{z}_i(t)$. He/she can potentially obtain new knowledge $\underline{z}'_i(t)$ by either innovation or imitation through another agent. Whether to adopt it and update his/her current method or discard the obtained new knowledge depends on the new hamming distant to the respective goal $\underline{\hat{z}}_i(t)$. If the new method shortens the Hamming distance between agent i's current method to its goal of the chosen task, then agent i will keep the new knowledge and update his/her method.

Adoption or rejection of the observed method is based on the Hamming distance criterion:

$$\underline{z}_i\ (t+1) = \begin{cases} \underline{z}'_i(t), & \text{if } D\left(\underline{z}'_i(t),\ \underline{\hat{z}}_i(t)\right) < D\left(\underline{z}_i(t),\ \underline{\hat{z}}_i(t)\right) \\ \underline{z}_i(t), & \text{if } D\left(\underline{z}'_i(t),\ \underline{\hat{z}}_i(t)\right) \geq D\left(\underline{z}_i(t),\ \underline{\hat{z}}_i(t)\right) \end{cases} \quad (4)$$

2.2.3 Choice Endogenization and Evolution Process

In Fig. 1, at stage one, if the chosen action brings the agent a new method that is closer to his/her goal, the agent will be more likely to choose that action again in the next period. At stage two, when the agent chooses imitation, he/she has to decide whom to imitate from. If the chosen agent j brings agent i closer to the goal, agent i will be more likely to choose agent j again in the next period. Thus, the probability of choosing innovation or imitation and the probability of choosing other person are both adjusted over time based on agent's past experience and reinforcement learning.

Denote $q_i(t)$ as the probability that agent i chooses to innovate while $1-\ q_i(t)$ as the probability that agent i chooses to imitate. Denote $p_i^j(t)$ as the probability that agent i is likely to imitate from agent j. Both $q_i(t)$ and $p_i^j(t)$ are endogenizing and adjusted over time based on reinforcement Bayesian algorithm.

The evolution process is a two-stage stochastic decision process with reinforcement learning. Stage one decides how likely the agent i will choose the previous action again while stage two decides how likely the agent i will choose the agent j to observe again.

In stage one, Experience-Weighted Attraction (EWA) (Camerer and Ho, 1999) learning rule is applied for adjusting agents' evolutionary actions. The probability $q_i(t)$ is adjusted each period on the basis of evolving attraction measures, $B_i^{in}(t)$ and $B_i^{im}(t)$, for innovation and imitation correspondingly. The evolution of $B_i^{in}(t)$ and $B_i^{im}(t)$ follow the process below:

$$B_i^{in}(t+1) = \begin{cases} \emptyset B_i^{in}(t)+1, & \text{if adopted} \\ \emptyset B_i^{in}(t), & \text{Otherwise.} \end{cases} \quad (5)$$

$$B_i^{im}(t+1) = \begin{cases} \emptyset B_i^{im}(t)+1, & \text{if adopted} \\ \emptyset B_i^{im}(t), & \text{Otherwise.} \end{cases} \quad (6)$$

Where $\varphi \in (0, 1]$.

Hence, if the agent choses to pursue innovation and then adopts the newly created knowledge, then the attraction measure for innovation increases by one after allowing the decay factor φ on the previous attraction level. Otherwise when unsuccessful (either failed or stayed idle, or successfully obtained new knowledge but it was not helpful), or chose to pursue imitation instead, the attraction measure for innovation is the attraction level from the previous period decayed by φ. Likewise, a success or a failure in imitation in period t has the same influence on Given $B_i^{im}(t+1)$, $B_i^{in}(t)$ and $B_i^{im}(t)$, one then derives the choice probability of innovation within period t as the following:

$$q_i(t) = \frac{(B_i^{in}(t))^{\lambda}}{(B_i^{in}(t))^{\lambda} + (B_i^{im}(t))^{\lambda}} \quad (7)$$

In stage two, the attractions and the probabilities are derived similarly. Let $A_i^j(t)$ be agent i's attraction to another agent j in period t. It evolves according to the following rule:

$$A_i^j(t+1) = \begin{cases} \emptyset A_i^j(t)+1, & \text{if adopted} \\ \emptyset A_i^j(t), & \text{Otherwise.} \end{cases} \quad (8)$$

where $\forall j \neq i$.

Hence, $p_i^j(t)$ is adjusted each period on the basis of the attraction measures, $\{A_i^j(t)\}_{j \neq i}$:

$$p_i^j(t) = \frac{(A_i^j(t))^{\lambda}}{\sum_{j \neq i}(A_i^j(t))^{\lambda}} \quad (9)$$

$\forall j \neq i$, $\forall i$, where $\lambda > 0$

Therefore, $q_i\ (t)$ and $p_i^j(t)$ are endogenously derived and they evolve over time in response to the individual's past experience in the rational way. Both endogenous and exogenous parameters are crucial for understanding knowledge creation, organizational structure, social learning and the collective performance is influenced by these parameters. Thus, the organization average level of innovation is measured as:

$$\overline{q}(t) = \frac{1}{M}\sum_{i=1}^{M} q_i(t) \quad (10)$$

2.3 Modeling the Turbulent Environment
2.3.1 Task Environment

As agents solving problems and moving closer to their goals, the goal vectors are also evolving. It is such change that makes knowledge creation and diffusion through a social network vital.

2.3.2 Group Division and Goal Scope

In the organization, M agents are provided with goal vectors that related to J groups, meaning different agents will have to solve different domain problems. Agents in the same group will face similar tasks which is essential to allow structure to emerge from the bottom-up. Fig. 2 illustrates the goal scope for the organization, groups and individuals.

2.3.3 Turbulence and Complexity

Denote $s \in \{0,1\}^{Nd}$, define $\delta(s,\kappa) \subset \{0,1\}^{Nd}$ as the set of points that are exactly Hamming distance k away from s. The set of points within Hamming distance k of s is defined as:

$$\Delta(s,\kappa) \equiv \bigcup_{i=0}^{\kappa} \delta(s,i) \tag{11}$$

$\Delta(s,\kappa)$ is a set whose "center" is , s and k is the intra-group tightness of goals. Suppose there are J groups in the organization and M agents are randomly and evenly distributed into groups. Let a_k be the set of agents belonging to group $k \in \{1,2,\dots,J\}$. Denote g_k as the seed vector used to generate the initial goal vectors for all agents in a_k,

$$\underline{\hat{z}}_i(0) \in \Delta(g_k,\kappa)\ \forall i \in a_k,\ \forall k \in \{1,2,\dots,J\} \tag{12}$$

All agents in a_k then have goal vectors which lie within Hamming distance k of the group seed vector g_k The diversity among groups is modeled by allowing their group seed vector varies. Denote organizational goal seed vector U and randomly select the group seed vectors from $\Delta(U,X)$. The inter-group tightness of the goals is controlled by X, which is the maximum Hamming distance between a group seed vector and the organization seed vector. The intra-group tightness of goals is controlled by κ. For example, if J=2, the two group seed vectors are randomly chosen from the set $\Delta(U,X)$. Taking the seed vector for group 2, g_2, $\Delta(g_2,\kappa)$ is the set of vectors that are within Hamming distance k of g_2. The initial goal vector for agent i, $\underline{\hat{z}}_i(0)$, is then an element of this set.

In period t, agent i has the current goal vector of $\underline{\hat{z}}_i(t)$. In period $t+1$, his/her goal stays the same with the probability σ and changes with the probability $(1-\sigma)$. The shifting dynamic of the goal vector is guided by the following stochastic process. The goal in period $t+1$, if different from $\underline{\hat{z}}_i(t)$, is then chosen *iid* from the set of points that lie both within the Hamming distance ρ of $\underline{\hat{z}}_i(t)$ and within Hamming distance κ of the original group seed vector g_k. Hence, defining $\wedge(\hat{z}_i(t), \rho, g_k\kappa)$ as the set of points from which the goal in $t+1$ is chosen, we have

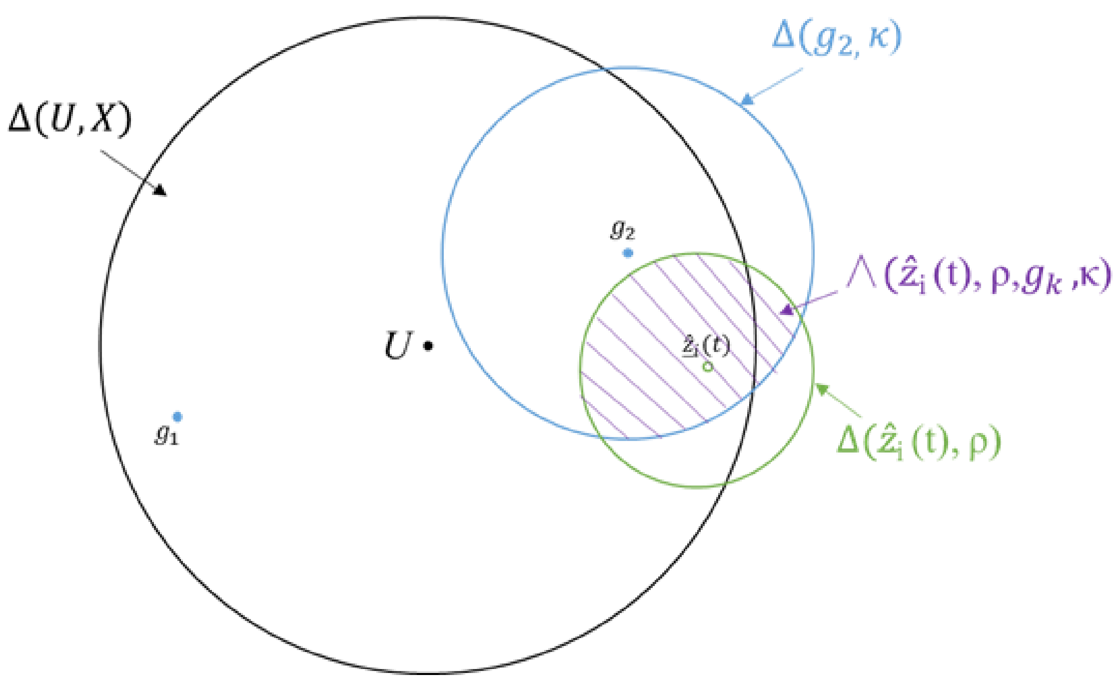
$$\wedge(\underline{\hat{z}}_i(t), \rho, g_k, \kappa) \equiv (\Delta(\underline{\hat{z}}_i(t), \rho) \setminus \underline{\hat{z}}_i(t))\, \Delta(g_2 \cap \kappa) \tag{13}$$

Fig. 2 shows $\wedge(\underline{\hat{z}}_i(t), \rho, g_k, \kappa)$ as the shaded area which is the intersection of $\Delta(\underline{\hat{z}}_i(t), \rho)$ and $\Delta(g_2, \kappa)$, excluding $\underline{\hat{z}}_i(t)$. Consequently,

$$\begin{cases} \hat{z}_i(t+1) = \hat{z}_i(t) & \text{with probability } \sigma \\ \hat{z}_i(t+1) \in \wedge(\hat{z}_i(t), \rho, g_k, \kappa) & \text{with probability } 1-\sigma \end{cases} \tag{14}$$

Where σ stands for stability of the environment

FIGURE 2
SCOPE OF INTRA-GROUP VS. INTER-GROUP TIGHTNESS OF GOALS.



The goal vector for agent i who belongs to group k then stochastically fluctuates while remaining within Hamming distance ρ of his current goal and Hamming distance k of the group's initial seed vector. The former condition allows us to control the possible size of the change while the latter condition allows us to maintain the intra-group tightness of goal. The inter -temporal goal variability ρ can also be considered as the bits that flips with probability $1-\sigma$. The lower the σ and the greater the ρ, the more frequent and turbulent is the change, respectively, in an agent's goal vector. The higher the k, the lower the intra-group goal congruence is. The higher the X, the greater the inter-group diversity in terms of their goals is.

2.4 Measurement of Organizational Structure

Shannon's (1948) Entropy $E_i(t)$ is employed to measure the network concentration when individual agents engage in imitation by acquiring shared knowledge. In the model, $p_i^j(t)$ denotes the probability that agent i choose agent j for social learning. At the beginning, when there is no social order in the organization as imitation is completely random, the probability of each individual to choose anyone else in the organization is equal, thus $p_i^j(t) = 1 / (M-1)$. Alternatively, as time proceeds, when someone concentrates on a single agent for imitation, then $p_i^j(t) = 1$. The organizational structure emerges from bottom-up and gradually stabilizes.

The entropy $E_i(t)$ is defined as:

$$E_i(t) \equiv - \sum_{\forall j \neq i} p_i^j(t) \cdot \log_2 p_i^j(t) \tag{15}$$

It can range from 0 to $\log_2(M-1)$. The larger the value, the less concentrated the network is.

2.5 Simulation Design and Results

2.5.1 The baseline setting

In the organization, there are $M = 6$ agents equally distributed in $J = 2$ two groups. For the baseline setting, $\mu_i^{in} = 0.5$ and $\mu_i^{im} = 0.5$ is designated, so under 50% probability that new knowledge can be created by innovation or other's knowledge can be acquired by imitation through the network. Listed in Table 1, μ_i^{in}, μ_i^{im}, φ, and λ govern an agent's decision-making behavior while X, κ, ρ, and σ control the task environment. The stability of the environment is set to be σ = 75% which means under 25% probability the agent's goal will shift, and two or less randomly selected bits of the goal will flip because $\rho = 2$. The organizational inter-group rightness of goals is $X = 16$ while the intra-group tightness of goals is $\kappa = 8$ which indicates two groups have considerably different tasks, hence the emerged organizational structure can be more easily observable. The agent's attraction to either innovation or imitation at t = 0 is set to be 1 with $B_i^{in}(0) = B_i^{im}(0) = 1$, hence the agent is initially equally attracted to either action. For imitation, agent's attraction to another agent at $t = 0$ is also set to be 1 with $A_i^j(0) = 1$, hence the agent is initially equally attracted to others. The attraction decay factor and the agent's sensitivity to attraction are set to be fixed with $\varphi = \lambda = 1$, because the purpose of baseline simulation is to explore how organizational performance is influenced by individual's action and how structure is emerged from the bottom up.

2.5.2 Experimenting Different Parameters

To explore how the steady-state behavior of the organization is influenced by different innovation productivities and social learning reliabilities, several experimentations with the developed model are carried out with the settings listed in Table 2. Each steady-state performance of the organization $\bar{\pi}$ is calculated and compared. Game 1 and Game 2 are performed to observe the organizational performance and emergence of

TABLE 1
NOTATIONS OF BASELINE SIMULATION SETTING.

Notation	Definition	Baseline Value
M	Number of agents	6
J	Number of groups	2
t	Time steps	10,000
μ_i^{in}	Innovativeness of agents	0.5
μ_i^{im}	Reliability of social learning	0.5
X	Inter-group tightness of goals	16
κ	Intra-group tightness of goals	8
ρ	Inter-temporal goal variability	2
σ	Stability of the environment	0.75
φ	Attraction decay factor	1
λ	Agent's sensitivity to attraction	1
$B_i^{in}(0)$, $\forall i$,	i's attraction to innovation at t=0	1
$B_i^{im}(0)$, $\forall i$	i's attraction to imitation at t=0	1
$A_i^j(0)$, $\forall i$, $\forall j \neq i$	i's attraction to j at t=0	1

organizational structure. Since there is no significant difference in results between Game 1 and Game 2 after the simulation, then Game 2 is selected as the baseline simulation representative. Meanwhile, to explore the inter-group learning and the intra-group learning among agents, 20 replications of each t = 10,000 simulation are carried out and the results are averaged where all variables are refreshed each time including the initial settings.

2.5.2 Simulation Results

As shown in Fig. 3a, the organizational performance is greatly improved through agents' effort on creating new knowledge and sharing existing knowledge. Then it is maximized and stabilized. Meanwhile, the organizational structure also emerged from the bottom up and stabilized as the entropy decreases (Fig. 3b). After repeating the same simulation for 20 times, the averaged social learning probability $p_i^j(t)$ are calculated and plotted in Fig. 4. The lighter the color, the higher the probability $p_i^j(t)$ and the stronger the learning is. The black grids on the diagonal indicate agents do not learn from themselves, while the light grids indicate a strong social learning from agents on the horizontal axis to the ones on vertical axis. For example, number 3 agents on horizontal axis is highly likely to learn from number 2 agent on the vertical axis. A strong intra-group learning is identified since two-group structure can be intuitively observed in Fig. 4. One of the striking findings is that organizational performance is not monotonically improved by either innovation or imitation. After repeating the simulation and experimenting with different parameters listed in Table 2, Game 3 to Game 6's steady-state

TABLE 2
EXPERIMENTING DIFFERENT PARAMETERS.

Games	Innovation (μ^{in}) Productivity of New Solution	Imitation (μ^{im}) Reliability of Social Learning
Game 1	80%	80%
Game 2	50%	50%
Game 3	25%	5%
Game 4	25%	30%
Game 5	25%	50%
Game 6	25%	80%

FIGURE 3A
ORGANIZATIONAL PERFORMANCE

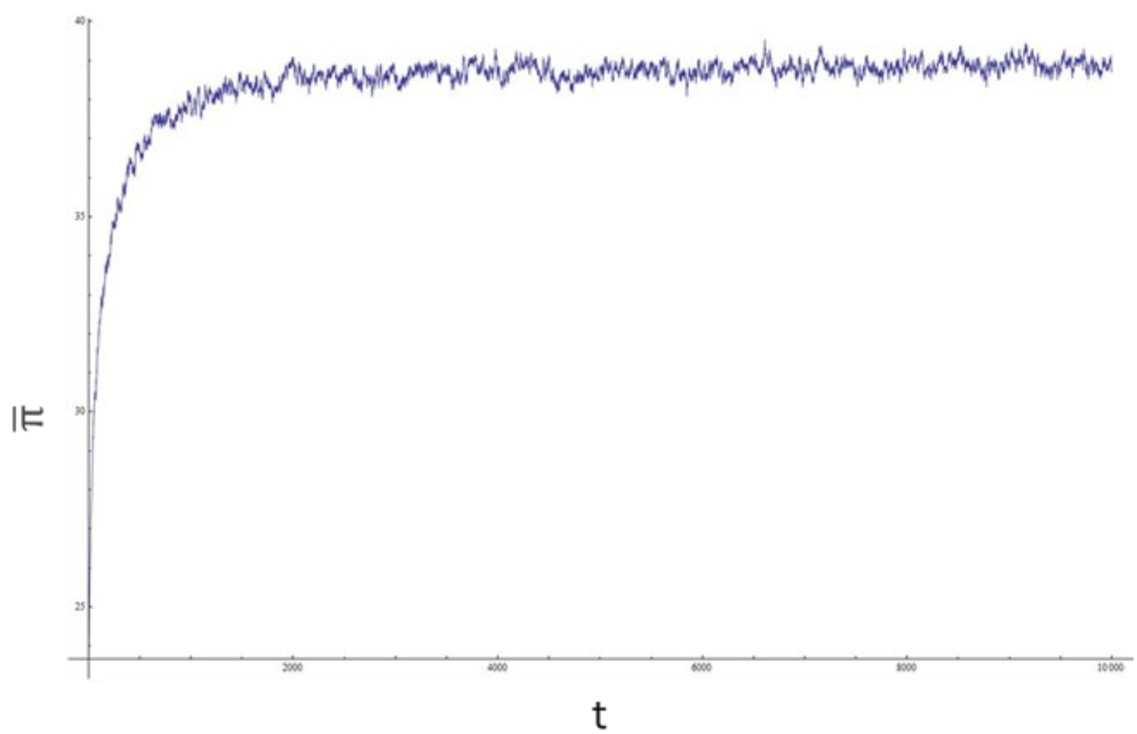


FIGURE 3B
ENTROPY OF STRUCTURE FORMATION

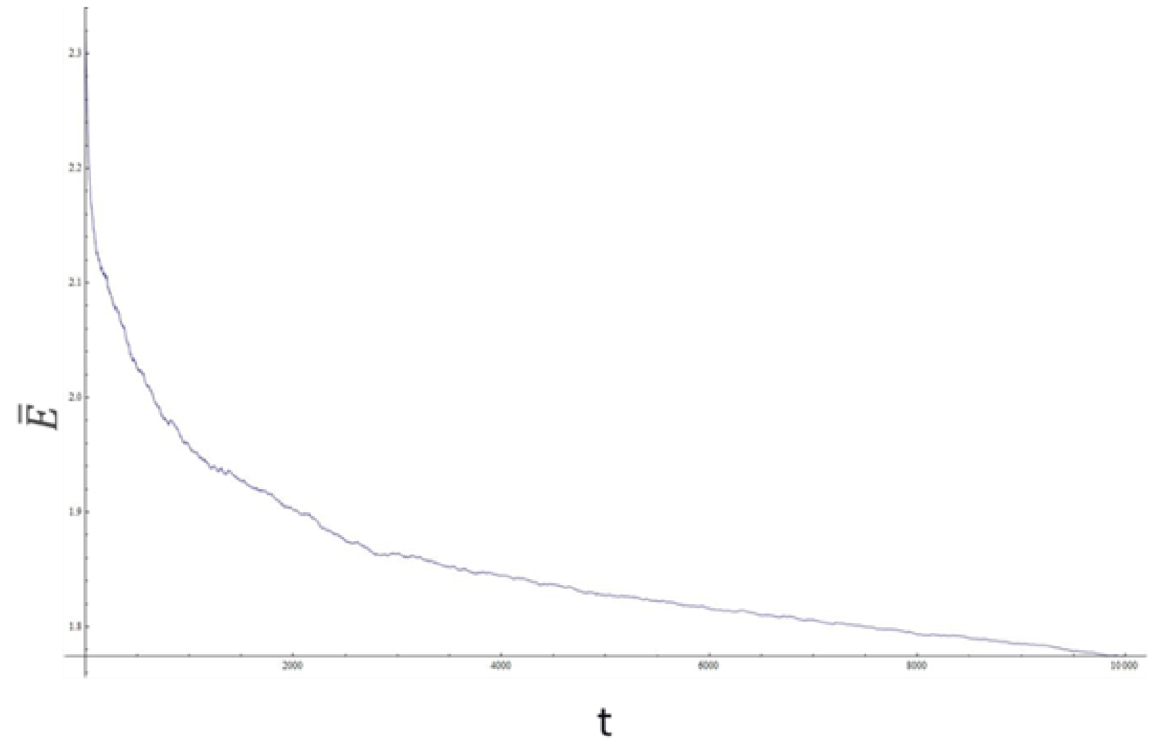
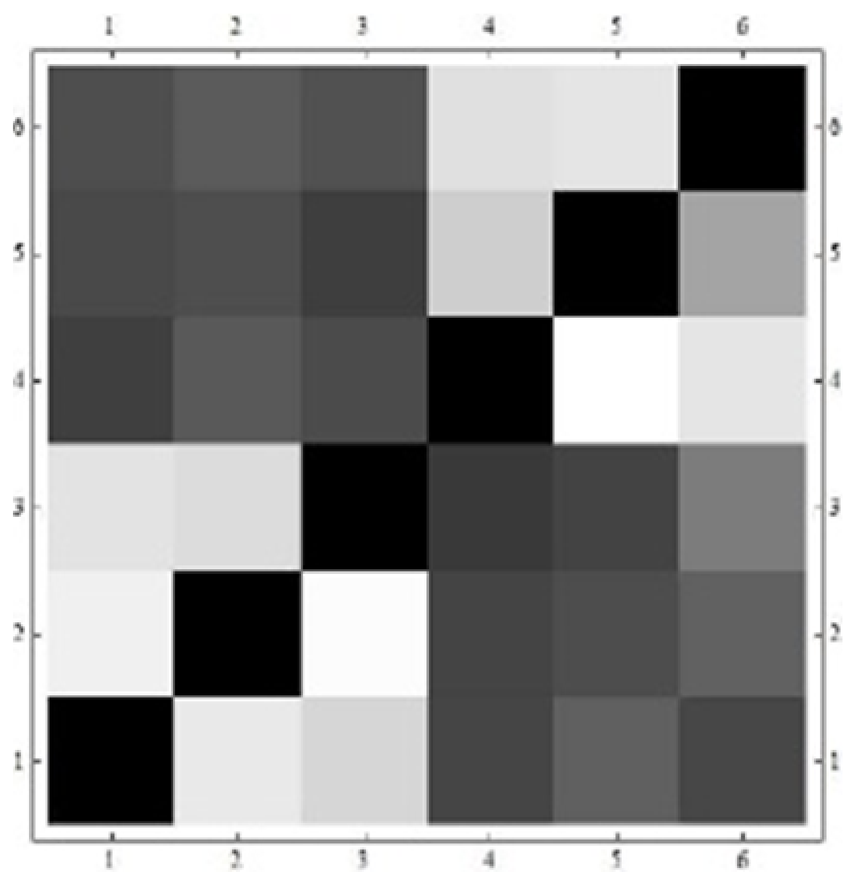


FIGURE 4
INTRA-GROUP LEARNING VS. INTER-GROUP LEARNING.



organizational performance are calculated and plotted in Fig. 5, revealed non-monotonicity in organizational performance.

THE EXPERIMENT

3.1 The Computer-Aided Game

The purposes of the gamified computer-aided human experiment include validation of the developed multi-agent model; observation of human behavior in reality for improving the multi-agent model in future; and identification of potential factors that may potentially and crucially influence human decision making and organizational performance.

3.2 Implementation

The experiment is gamified and designed as an online challenge. Each participant has to compete with one another in order to gain the highest score. The computer-aided platform is developed with initial settings complied with the agent-based model. Since the timespan in experiment is completely different with the simulation, deciding how many rounds for each game in achieving steady-state organizational performance is crucial, hence, several trial games were played and tested. Finally, 80 rounds for Game 1 to 2 while 200 rounds for Game 3 to Game 6 are determined, since they are economically sufficient to reach steady-state organizational performance. Meanwhile, in order to shorten the searching and testing time when forming strategy on either innovation or imitation, each participant is informed with μ^{in} and μ^{im} value in advance. They are also clear that participants

FIGURE 5
NON-MONOTONICITY

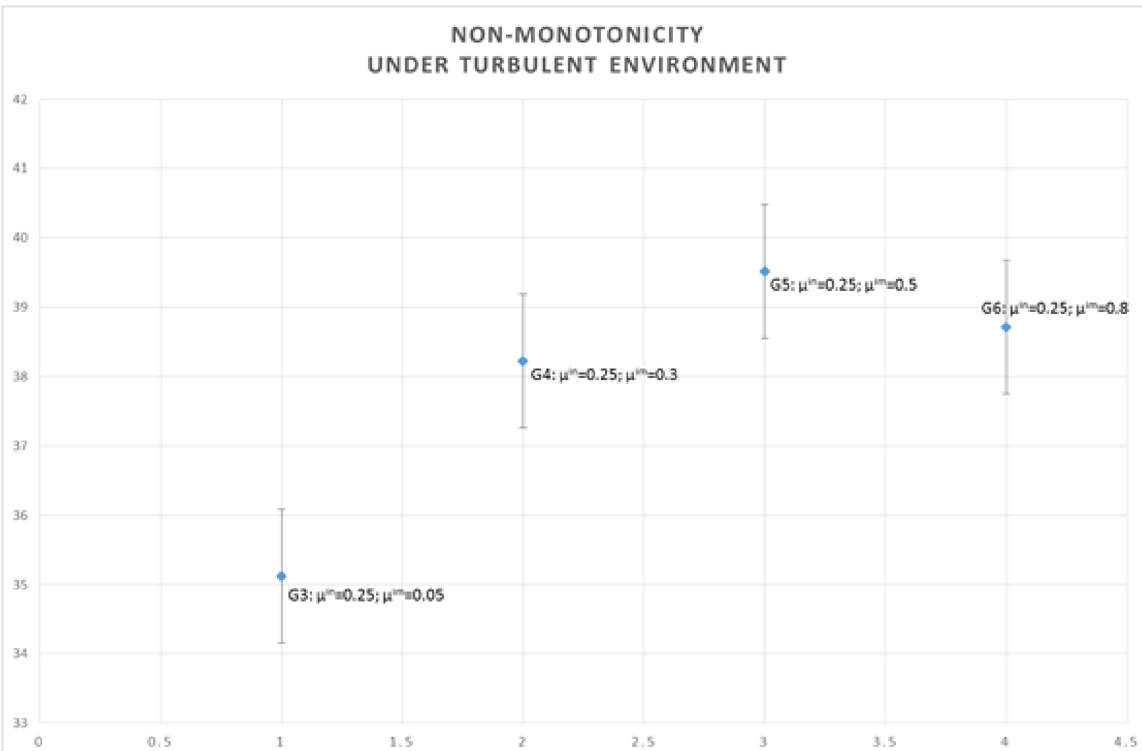


FIGURE 6
SNAPSHOTS OF THE EXPERIMENT GAME.

in the same group are assigned with similar tasks while participants in other group have very different tasks. Hence they know intra-group learning will be more helpful than inter-group learning. Two selected snapshots of the online challenge are shown in Fig. 6.

There were six games in total played with different parameters assigned as shown in Table 2. In total, thirty-six volunteered students participated in the experiment games.

3.3 Results of the Experiment Games

The results indicate that along with participants' effort on innovation or imitation, the collective performance is improved significantly. Then it reaches a peak and stays stabilized (Fig.7). This is aligned with the simulation.

At the steady state, the structure is emerged (Fig. 8), indicating that workers with similar goals hold higher tendency to learn among each other instead of reaching out for other solutions. In the diagram, the bubble size indicates the times players on horizontal axis chose players on vertical axis. The larger the bubble, the stronger the social learning is. Two distinct groups A and B can be intuitively identified. Although there is noise, the majority of the data matches the simulation result.

After the completion of game 3 to game 6, each steady-state collective performance value is calculated and plotted in Fig. 9 indicating non-monotonicity as well. This means that under a fixed innovation productivity, gradually increasing the reliability of the social learning can enhance the collective performance until a certain point. However, when further increased, it can be harmful to the collective performance since workers favor the engagement in social learning instead of new

FIGURE 7
COLLECTIVE PERFORMANCE IN THE EXPERIMENT GAME.

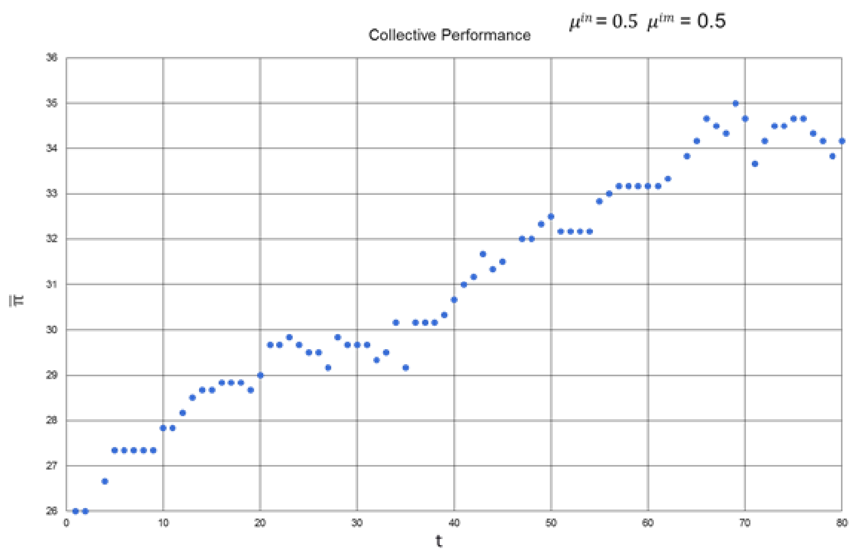
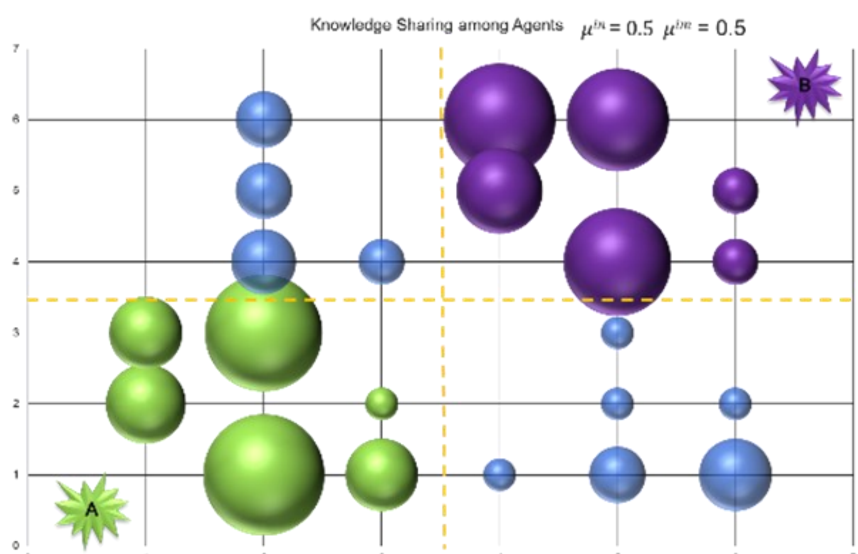


FIGURE 8
EMERGED SOCIAL STRUCTURE AND SOCIAL LEARNING.



knowledge creation for solving new problems under the turbulent environment.

DISCUSSION

4.1 Why Non-Monotonicity Happens?

Surprisingly, results from both simulation and experiment show non-monotonicity in organizational performance. This means that organizational performance is not enhanced and optimized by either innovation or imitation alone, but both. When the innovativeness of individuals is fixed to μ^{in}=25%, increasing social learning reliability incrementally from μ^{im} = 5%, μ^{im}=30%, μ^{im}=50%, to μ^{im}=80% not always allows the organizational performance to continuously strike. Both the simulation and the experiment reveal a peak in the organizational performance at G5: μ^{in}=25%; μ^{im}=50% and a severe decline at G6: μ^{in}=25%; μ^{im}=80%. Now the question is why it happens. Shouldn't the organizational performance be continuously striking and improving since the social learning is getting more reliable? This phenomenon can be explained as the following. When social learning reliability is increasing, agents tend to engage more in social learning sharing existing knowledge among one another rather than creating new knowledge by innovation to solve new problems. When there is not enough new knowledge created in the organization for the new problem, the organizational performance declines. This non-monotonicity phenomenon indeed depends on the turbulence of the environment. The more turbulent the environment, the higher probability the organization will face challenges when most agents engage in imitation. To prove this hypothesis, another set of simulation was carried out under the stable environment. This time, the stability of the environment σ is tuned from 75% to 95%, while the inter-temporal goal variability ρ is tuned from 2 to 1 which indicates that 1 randomly selected digit in goal vector flips when goal shifts under probability $1\text{-}\sigma$. This allows the environment to be stable for the organization. Under such design, four more simulations were carried out with fixed μ^{in}=25%, and gradually increased social learning reliability from μ^{im} = 5%, μ^{im}=30%, μ^{im}=50%, to μ^{im}=80%. The result shown in Fig. 10 indicates the organizational performance under the stable environment continuously strikes without any decline because not much new challenge is brought to the organization. Fig. 5 is posted again with Fig. 10 for easier comparison.

4.2 Unique Characteristics and Advantages of Simulation and Experiment

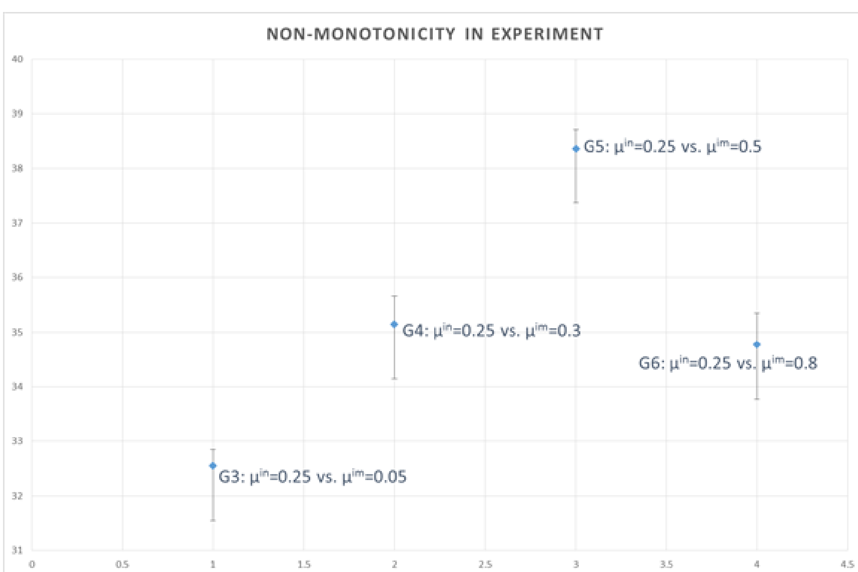
4.2.1. Robustness of Simulation

One of the unique characteristics and advantages of multi-agent simulation is the robustness. It can produce emerged macro level phenomenon based on the micro individual interactions and offer both process and state scalable view of results for investigation. In this study, the simulation discovers the non-monotonicity in organizational performance which cannot be possibly achieved using traditional costly and time consuming qualitative or quantitative methodologies. Based on such a versatile tool, organizations can design new strategies and policies, especially suitable for coping complex and turbulent competitive environment as problems become obsolete quickly and unpredictably. Meanwhile, unlike field work methodologies, the simulation does not need any pre-requisite, sacrifice overhead cost, interrupt organizational daily operation or introduce panic to employees. Hence, it can be used as a desirable alternative for organizations managing knowledge under complex and uncertain environment.

4.2.2 Advantages of Gamified Experiment

Experiment offers rich empirical information including human behavioral decision making in the real situation. Unlike computer agents, human beings are not always stringently rational. As shown in Fig.8, only player 1 on the horizontal axis learn intra-grouply all the time while others are all not, even given the information intra-group learning is more helpful. The rest players all attempted giving inter-group a try. Surprisingly player 6 on the horizontal axis learned more inter-grouply than

FIGURE 9
COLLECTIVE PERFORMANCE IS NON-MONOTONICALLY IMPROVED BY EITHER INNOVATION OR IMITATION



intra-grouply. Whether the irrational behaviors are due to the curiosity, social preference or heuristic bias, so far it cannot be certain. Yet, it suggests a need for revising the action evolution reinforcement learning rule in the agent-based model. Therefore, the gamified experiment provides crucial evidence for model improvement.

4.2.3 Power of Integration

The simulation serves as a roadmap for the experiment while the experiment validates and refines the developed agent-based model with supplementary information from the reality. Although simulation and experiment can be used as self-contained methodology, when integrated as in this study, both can reinforce and elevate each other delivering more powerful, flexible and reliable results.

CONCLUSION AND FUTURE WORK

In summary, the simulation offers rich and scalable results indicating with agents' effort on either knowledge creation or diffusion, the organizational performance is swiftly enhanced. The organizational structure emerged from the bottom-up and stabilized gradually. Knowledge diffusion and social learning is more frequently observed intra-grouply than inter-grouply. Due to the uniqueness and robustness of the simulation, non-monotonicity in organizational performance has been discovered. Results from the gamified experiment prove the developed multi-agent model reliable and effective. However, several interesting points on human heuristics and decision making behaviors are observed which may potentially influence the organizational performance. For instance, human participants are not always rational when choosing the action. In other words, the reinforcement learning may not be suitably applicable. Hence, the evolution process of agents' action needs to be modified in the future modeling work.

Through the multi-agent simulation and the gamified experiment, a profound alternative knowledge management methodology has been demonstrated. The organizational knowledge creation and diffusion is successfully modeled through a multi-agent simulation and validated by the gamified computer-aided human experiment. The study examines how agents' behaviors at the micro level affect organizational performance and structure at the macro level. With such robust and practical approach, further organizational policy can be designed and tested without prerequisite or sacrificing overhead cost. The findings suggest further work should focus on how agents' heuristics influence the organizational performance. Since the current model does not introduce competition among individuals, it may also be an important factor that affects the individual decisions and organizational performance.

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FIGURE 5
NON-MONOTONICITY
UNDER TURBULENT ENVIRONMENT

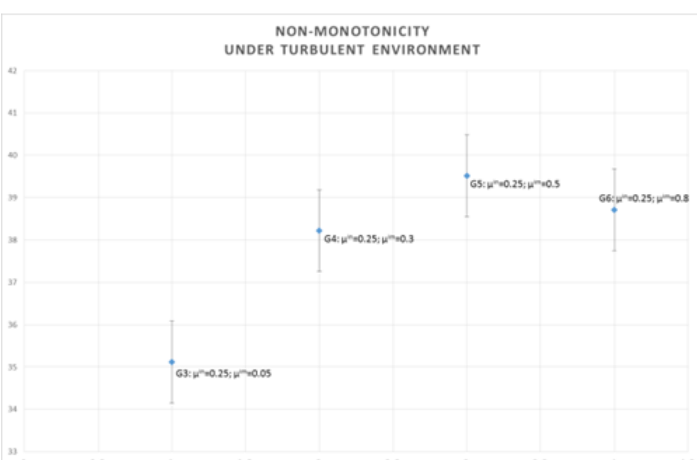

FIGURE 10
MONOTONICITY UNDER
STABLE ENVIRONMENT