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A Study of Organizational Knowledge Management with Agent-Based Modeling and Behavioral Experiments

(エージェントベースモデリング及び行動実験による組織的ナレッジ・マネジメントの研究)

顧　潔

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ABSTRACT

This study lies in the field of knowledge management (KM) which has been formally established as a discipline in 1990s to achieve organizational objectives by making the best use of knowledge. Knowledge is critically important because it is regarded as fundamental source for value creation and competitive advantages in the rapidly proliferating knowledge-based economy. KM facilitates decision-making, builds learning culture, and improves organizational performance ultimately.

Conventional KM approaches are neither effective nor capable to handle growing complexities and unfathomability due to three inadequacies, namely ignorance of the environmental uncertainties, negligence of human bounded rationality, and missing micro-macro links for gaining holistic picture and understanding causalities on evolutionary and emergence perspectives.

To overcome the limitations, primary goals of this study aim at developing a methodology for evolutionary and behavioral KM which has not yet be attempted in the past;

elucidating the microscopic KM impact on the macroscopic organizational outcomes; and evaluating KM policies with a consideration of environmental uncertainty and agents' bounded rationality. Additional goals are to demonstrate the practicability of the methodology, to induce a KM incentive system as an administrative KM strategy, to investigate how social interaction and interdependency of agents impact the organizational outcomes, and to explore various administrative interventions and corresponding effectiveness. Hence, it paves the way for establishing a new field of study on evolutionary and behavioral KM ultimately.

In this study, a basic KM game concerning environmental uncertainty and human bounded rationality as well as an extended KM game concerning incentive system and social interactions are developed accordingly then implemented in agent-based simulation and behavioral experiments iteratively. In the basic KM game, agents have to solve problems and strike for better performance strategically under an uncertain environment by choosing either Innovation (creating new knowledge independently) or Imitation (acquiring shared knowledge through establishing social networks). The productivity of innovation and connectivity of social network are exogenous administrative KM policies, whereas the probability of choosing each KM strategy is adjusted overtime by agents' endogenous adaptive learning. In the extended KM game, an incentive system is induced as administrative policy. Agents strategically make KM decisions under two dilemmas, namely loss aversion vs. risk seeking and competition or cooperation. Agents need to choose strategically between the maintenance of individual competitive advantage and optimization of collective outcomes. Overall, besides the emergent macroscopic organizational performance and structure, research findings also suggest a *non-monotonicity* on organizational long-term steady-state performance alongside the enhancement of social network connectivity, *a scarcity heuristic* on agent's decision making, and various administrative incentive interventions that are suitable for optimizing particular situations coping with agents' endogenous social interactions. Moreover, the most cost-effective intervention which motivates the individual to create more knowledge, unleash the innovation potential, while keeps a good cooperative culture has been identified.

This study is the first of its kind combining ABM simulation with behavioral experiments in the KM literature. The developed integrated methodology is capable in dealing with growing complexity, elucidating causal relationships, and offering a pragmatic platform for policy-makers to design and test the effectiveness of interventions and gain administrative insights without sacrificing overhead cost and cause panic or interruptions to daily operation.

In the future, the KM game will be further improved by incorporating the freewill, learning, and adaptation of the administrator, hence the co-evolution between the organization and member agents can be realized. Furthermore, the knowledge should enhance agents' cognition, behavior, and performance, meanwhile agents should re-shape, reuse, and renew the knowledge, whereas the organization whether through the administrator or itself should actively adjust the conditions that facilitate the dynamics and growth, so that the co-construction of the reality among knowledge, agents, and the organization will also be possibly achieved. By then, theory will be advanced, methodology will be sophisticated, and applications will be abundant.

PUBLICATIONS & AWARDS ARISING FROM THE THESIS

List of Book

1. Gu, J., Wang, H., Xu, F., & Chen, Y. (2016). Simulation of an Organization as a Complex System: Agent-Based Modeling and a Gaming Experiment for Evolutionary Knowledge Management. In *Simulation and Gaming in the Network Society* (pp. 443-461). Springer Singapore.

2. Gu, J., Lee, W.B., & Lui, C.C.Y. (2010). A Case Study of Knowledge Elicitation on Intellectual Capital Performance in the Fund Service Industry. *Case Studies in Knowledge Management Research*, 64-84, Academic Publishing International.

List of Journal Paper

1. Gu, J. & Chen, Y. (2016). Knowledge Creation and Diffusion Dynamics under Stable and Turbulent Environment for Organizational Performance Optimization, *International Journal of Industrial and Manufacturing Engineering*, Vol:3, No:2, 853-859.

2. Gu, J., & Chen, Y. (2015). Simulation and Experimental Study of Knowledge Management in Organization. *Developments in Business Simulation and Experiential Learning*, Vol: 42, 269-279.

3. Gu, J., Lee, W.B., Tsui, E., Cheung, C. F., Wang, W.M. (2011). Discovery and Capture of Organizational Knowledge from Unstructured Information. *International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering*. Vol: 5, No:5, 520-525.

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5. Gu, J., & Chen, Y. (2015). Simulation and Experimental Study of Knowledge Management in Organization. *In Proceedings of The 42nd Association for Business Simulation and Experiential Learning (ABSEL) Conference*, Las Vegas, USA.

6. Gu, J., & Chen, Y. (2014). A Simulation and Gamification Approach of Organizational Knowledge Management, *In Proceedings of the 6th Academic Conference on Systems Innovation*, Tokyo, Japan.

7. Gu, J., Wang, H., Xu, F.J., Chen, Y. (2014). A Study of Knowledge Creation and Sharing in an Organization by Using Multi-Agent Simulation and a Computer-Aided Human Experiment, *In Proceedings of Fourteenth International Conference on Knowledge, Culture and Change in Organizations*, Oxford, UK.

8. Gu, J., Lee, W.B., Tsui, E., Cheung, C. F., Wang, W.M. (2011). Discovery and Capture of Organizational Knowledge from Unstructured Information. *World Academy of Science, Engineering and Technology (WASET 2011)*, Paris, France.

9. Gu, J., Lee, W.B., & Lui, C.C.Y. (2010) A Case Study of Knowledge Elicitation on Intellectual Capital Performance in the Fund Service Industry. *In Proceedings of the second European Conference on Intellectual Capital (ECIC 2010)*, Lisbon, Portugal.

List of Talk

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CHAPTER 1 INTRODUCTION

This chapter provides an overview of the thesis. It introduces the knowledge management (KM) as a self-contained discipline in organizational studies. Three major limitations of the conventional approaches have been pinpointed that ignite the future KM direction, especially on coping with the growing complexity and environmental uncertainty, human behaviours, and micro-macro links in a social organization. The research motivation arises as an attempt to tackle problems identified in a scientific and pragmatic manner by proposing an integrated KM approach. The significance of the study is also highlighted. At the end of this chapter, the organization of the thesis is presented.

1.1 Background of the Study

In the knowledge-based theory of organization, knowledge replaces labor and capital as fundamental resources for competitive advantage and value creation (Andriessen, 2004; Addicott et al., 2006), not only for organizations, but also for nations and regions (Toffler, 1990; Drucker, 1993). Knowledge Management (KM) has been formally established as a multi-disciplinary field of study in 1991 for achieving organizational purposes by making the best use of knowledge (Nonaka, 1991).

1.2 Problem Statements

Due to the advancement of information technology, the growing social interactions, turbulent environment, and shortening of knowledge life cycles have contributed to the growing complexity and uncertainty of the workplace and put great pressure on administrators for establishing tailored-made KM policies that can effectively optimize the organizational outcomes. The Delphi Group offered survey evidence of the fast growing complexity that common organizations face (Delphi Group, 2012). The survey indicates a dramatic change in the characteristics of knowledge work and increasing complexity causes uncertainties for decision-making in today's knowledge economy. It also implies great opportunity on utilizing complexity for boosting performance advantage. Fully grasping the whole picture of the knowledge creation and diffusion is indeed a very difficult task due to human cognitive limitations. Many KM initiatives are unsuccessful because of the failure to identify the systemic determinants, interdependency, or causality.

KM has been fueled by methodologies such as questionnaire survey, observation and interviews, sense-making narratives, case studies and social network analysis. Numerous advanced data and information technologies or decision support systems (DSS), e.g. expert systems, also support knowledge workers' daily operation in organizations.

Difficulties have been identified in both theory advancement and industrial applications for linking KM with organizational outcomes under a complex and uncertain environment. Specifically what microscopic efforts lead to the macroscopic phenomena, how it is evolved overtime through social interactions, and what conditions that create unexpected results are unknown. For conventional approaches, content-orientation and technological precision are over-emphasized than overall managerial effectiveness. Technology is particularly suitable for offering practical solutions to boost productivity as a part of the whole. It does not consider the systemic reactions, environmental turbulence, feedbacks or consequences. It is just like replacing a better heart in the body, claiming to be more efficient in plumping blood, but it may be harmful to the body or causing side-effect. The theoretical or scientific aspect of KM is still inadequate. Additionally, approaches which address human behavior aspect of KM and how aggregate individual behaviors are amplified over time through social interactions via systemic micro-macro links are barely found in the KM literature (Alavi and Leidner, 2001; Liao, 2003; Kakabadse et al., 2003; Kane et al., 2005; and Xu et al., 2008; and Nemani, 2009). Moreover, the perturbation is unavoidable in conventional approaches. For example, when researchers conduct the investigation in the organization, the daily operation is interrupted, undesired panic and stress is introduced upon employees, and the purpose of study maybe wrongly interpreted.

In other words, the ways by which data are collected, analysed and evaluated in conventional methodologies can be highly perceptual, subjective, and often political since the traditional approach ignores the holistic alignment with organisational objectives when selecting only a few processes for examination. This is why human are unable to see the complex reality of KM in a clear and holistic manner. Hence, the results can be highly unreliable. Meanwhile, in order to capture the complexity of the organizational KM, conventional approaches cost intensive manpower and long time. Therefore, they are neither adequate nor efficient. When dealing with complexity, old linear ways of seeing things are dangerous. A pioneer in education Jörg (2004) argues that complexity theory and system thinking may be helpful to escape from the old ideas and blind spots of social sciences and system science, and build up a new science – a science which may be of help in dealing with the complexity of reality as we may view it and experience it in the practice of knowledge interaction.

In summary, three major limitations are identified in conventional KM approaches that are of great interst in this study:

(1) Limitation in coping with growing complexity and environmental uncertainty in a holistic manner and explaining the non-linear causality.

(2) Limitation on ignorance of the human behavioral KM decisions

(3) Limitation on missing micro-macro links and consequences

1.3 Research Opportunities and Motivation

To overcome the limitations and tap into the complexity paradigm for next generation KM development in a holistic manner, the newly and rapidly popularized agent-based simulation is considered to be a promising solution. An agent-based model (ABM) is a computer model for simulating autonomous agents and assessing the system as a whole based on the generated effects from agents' interactions. ABM is a kind of microscale model (Gustaffsson and Sternad, 2010) that is used in simulating the simultaneous operations and interactions of multiple agents in an attempt to re-create and predict the appearance of complex phenomena. ABM offers the possibility of modeling individual heterogeneity, representing explicitly agents' adaptive rules for decision making, generating social interaction and evolution, and situating agents in a geographical or another type of space (Gilbert, 2008). Its favorable features include modularity, great flexibility, large expressiveness and possibility to execute in a parallelized way (Taber and Timpone, 1996). Therefore, it fits the niche when simulating an organization as a complex adaptive system and examining the KM evolution are desired.

1.4 Research Objectives

The ultimate goal is to stablish a new field of study on evolutionary and behavioral KM for organization, especially on tackling the growing complexity and uncertainty. To pave the way for this goal, the primary objectives of this research are:

(1) To develop a methodology for evolutionary and behavioral KM;

(2) To elucidate the microscopic KM impact on macroscopic organizational outcomes;

(3) To evaluate KM policy with environmental uncertainty and agents' bounded rationality.

To be specific and concrete, a basic KM game that extracts the essence of the microscopic agents' KM behaviors and social interactions with endogenous freewill, incorporates exogenous administrative KM policy interventions, and link the organization with environmental uncertainty is to be developed; it will be then implemented in both agent-based simulation and behavioral experiments for obtaining static and dynamics, results; and some implications from the findings will be discussed. In addition to the development of the basic KM game, this study also aims at extending the work with an inducement of an incentive system and freewill for social interactions. Therefore, the additional objectives of this research are:

(1) To establish a conceptual framework for the inducement of incentive system under

two dilemmas namely: loss aversion vs. risk seeking and competition vs. cooperation for preserving and promoting diversity;

(2) To investigate how social interactions and interdependencies of agents impact on organizational outcomes;

(3) To explore various administrative interventions and evaluate the effectiveness accordingly.

1.5 Originality and Significance

This research work is the first of its kind combing agent-based simulation with behavioral experiments in the KM discipline. It offers a powerful and rigorous methodological alternative to cope with growing complexity that conventional approaches are unable to. It delivers descriptive and prescriptive outcomes including state and dynamics, long term and short term development, evolution and behaviors, etc., for organizational policy makers to experiment administrative interventions, forecast consequences, generate unforeseeable emergence, and evaluate the managerial effectiveness easily. It serves as a roadmap that make the cause and effect more understandable, hence, new organizational theories can be derived. In summary, this study bridges the theoretical, methodological, and practical gap in the KM literature.

1.6 Organization of the Thesis

The dissertation consists of seven chapters. Chapter One outlines the background of the study, problem statements, research objectives, and originality of the work. Chapter Two firstly reviews the literature of knowledge management as a self-contained discipline and secondly extends the notion with complexity theory, behavioral economics, and micro-macro link sociology theory towards a transdisciplinary development. Then the integrated KM approach is proposed and the research roadmap is presented in Chapter Three depicting a holistic organization KM as a complex adaptive system. In Chapter Four, the basic KM game is presented, the implementation in both ABM simulation and behavioral experiments are explained in details, results elucidate the microscopic KM effort impact on macroscopic outcomes under both exogenous KM policy and environmental influences; *non-monotonicity* in steady-state organizational performance alongside the enhancement of social network connectivity; and *scarcity heuristic* on agents' KM decision-making are revealed. In Chapter Five, the extended KM game is developed with an inducement of a KM incentive system to explore how agents strategically make KM decisions under two dilemmatic scenarios, namely loss aversion vs. risk seeking and competition or cooperation, and to investigate how the social interaction and interdependency of agents impact the organizational outcomes. Likewise, the extended

KM game is implemented in behavioral experiments then preliminarily prototyped in the ABM simulation. Chapter Six discusses the advantages of the integrated KM methodology, and how it can particularly serve the purpose of coping with growing complexity, environmental uncertainty, human bounded rationality, micro-macro links, and incentive system design. Last but not least, Chapter Seven concludes the dissertation by summarizing the achievements, highlighting the significance and impact, and suggesting possible opportunities for future work.

CHAPTER 2 LITERATURE REVIEW

In this chapter, the related literature concerning the research work is reviewed. The topics and concepts include: The general notion of organizational knowledge and knowledge management (KM); KM discipline development and evolution; Transdisciplinary KM with complexity theory, behavioral economics theory, and micro-macro link sociological theory. Then an integrated KM approach . It lays a theoretical foundation on the solution proposed in this study for overcoming the limitations and creating a paradigm shift for new KM study.

2.1 Organizational Knowledge Management

2.1.1 The Notion of Knowledge

In the knowledge-based view of the firm or the knowledge-based theory of organization (Conner, 1991; Demsetz, 1988; Conner and Prahalad, 1996; Kogut and Zander, 1992, 1996; Madhok 1996; Grant 1997; Nahapiet and Ghoshal, 1998; and Nickerson and Zenger, 2004), knowledge has replaced land, natural resources and labor as the ultimate source of value creation, and competitive advantages (Addicott et al., 2006; Lytras, 2006). The statement is also applicable for larger social systems like nations and regions (Toffler, 1990; Drucker, 1993). Although there is a great debate on defining knowledge as shown in Table 2-1, from various researchers, it can be seen that knowledge is considered either as information that has been analyzed and organized for solving problems and, making decisions or a set of insights, beliefs, experience, and judgments. Meanwhile Davenport and Prusak (1998) held a view that can integrate two perspectives, which is “knowledge is a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experience and information”. It habitudes not only in documents or repositories but also in organizational routines, processes, practices, culture and norms.

Table 2-1 Summary of Knowledge Definitions

Author	Definition of Knowledge
Webster's Standard Dictionary	Understanding gained from experience.
KM Institute	Knowledge is the understanding gained from experience, analysis and sharing. It gives us power to do something with data and information.
Army FM6-01.1	Knowledge is information analysed to provide meaning and value or evaluated as to implications for the operation. It is also comprehension gained through study, experience, practice, and human interaction that provides the basis for expertise and skilled judgement.
Woolf (1990)	Knowledge is the application of organized information to problem solving.
Turban (1992)	Knowledge is information that has been organized and analysed to make it understandable and applicable to problem solving or decision making.
Wiig (1993)	Knowledge consists of truths and beliefs, perspectives and concepts, judgements and expectations, methodologies and know-how.
Nonaka (1994)	Knowledge is created and organized by the very flow of information, anchored on the commitment and beliefs of its holder.
Van der Spek and Spijkervet (1997)	Knowledge is the whole set of insights, experiences and procedures that are considered correct and true and that therefore guide the thoughts, behaviours, and communications of people.
Beckman (1997)	Knowledge is reasoning about the information and data to actively enable performance, problem-solving, decision-making, learning and teaching.
Davenport et al. (1999)	Knowledge is information combined with experience, context, interpretation, and reflection.
Prusak (1999)	Knowledge is a human trait or attribute, distinguishing it from information in that only a human can obtain knowledge.

Liebowtiz and Beckman (1998) categorizes knowledge into three kinds: explicit, implicit and explicit. Explicit knowledge is often retained into formal and structured knowledge sources and is easily obtained and organized. Implicit knowledge is consider as being accessible through inquiry and discussion. Tacit knowledge is hidden in the human mind and consciousness which is accessible indirectly through practice, knowledge elicitation and observation of behavior. Further development suggests that knowledge can be generally classified into two categories: explicit knowledge and tacit knowledge (Nonaka and Konno, 1999). Explicit knowledge is knowledge that can be codified. It is easy to share and transfer between individuals and groups, whereas tacit knowledge is personal knowledge including skills, experience, know-how, intuition, and insights that are difficult to be formalized or shared among groups. Explicit knowledge includes databases, images, documents, guidelines, manuals and procedures. Knowledge sharing of explicit knowledge can be realized through communication. According to Nonaka (1994), tacit knowledge has both cognitive and technical perspectives. Cognitive perspectives are reflected by mental models in which people form concepts of the world, whereas technical elements can be expressed as know-how or skills. Knowledge sharing of tacit knowledge is comparatively more difficult than explicit knowledge, but it can be realized through a conversion into explicit knowledge first (Becerra-Fernandez and Sabhewal, 2001). Knowledge is abstract, vague, and difficult to quantify or measure, yet important to manage. Organizations must efficiently and effectively manage organizational knowledge in order to create intellectual capital and sustain competitive advantage (Hall, 1993; Powell & Dent-Micallef, 1997; Rumisen, 1998; Saka, 2002; Zack, 1999; Carroll & Tansey, 2000).

2.1.2 Knowledge Management (KM)

In the late nineteenth century, industrial practitioners and academic researchers started recognizing the significance of organizational knowledge, knowledge work and knowledge workers (Drucker, 1959; Popper, 1963; Polanyi, 1976). The term "Knowledge management" is firstly introduced by Karl-Erik Sveiby (1986) in his book "Knowledge companies" and Karl Wiig (1986) in an important KM article. Roughly at the same time, a Japanese veteran business guru, Ikujiro Nonaka, published a ground-breaking book in 1991 named *The Knowledge-Creating Company* (Nonaka, 1991). Since then, knowledge has increasingly become an important means for value creation and the most critical factor of competitiveness (Drucker, 1993; Nonaka and Takeuchi, 1995; Bogdanowitz and Bailey, 2002; Davenport, 2005; Mcdermott, 2005; Cooper, 2006; Tapscott, 2006). KM is seen today as a transdisciplinary practices (Wallace, 2007) and enables organizations to make the best use of knowledge.

However, there is no universal consensus on how KM should be defined. Different researchers hold different points of view of KM (Table 2-2). This is because KM is indeed rooted in and emerged from many disciplines.

Table 2-2 Summary of KM Definitions

Author	Definition of KM
Wiig (1993)	KM focuses on determining, organizing, directing, facilitating, and monitoring, knowledge related practices and activities to achieve the desired business strategies and objectives.
Hedlund (1994)	KM addresses the generation, representation, storage, transfer, transformation, application, embedding and protecting of organizational knowledge.
Marshall et al.,(1996)	KM is about generating, representing, accessing, transferring, embedding and facilitating knowledge and knowledge process developing a culture that values knowledge that shares, values and uses knowledge.
De Jarnet (1996)	KM is knowledge creation, which is followed by knowledge interpretation, dissemination and use, retention and refinement.
Sveiby (1997)	KM is defined as "the art of creating value from an organization's intangible assets".
Skyrme and Amidon (1997)	KM is the explicit and systematic management of vital knowledge and its associated processes of creation, gathering, organization, diffusion, use, and exploitation.
O'Dell (1997)	KM applies systematic approaches to find, understanding and use knowledge to create value.
Bassi (1997)	KM is the process of creating, capturing, and using knowledge to enhance organizational performance.
Snowden (1998)	KM can be defined as the identification, optimization and active management of intellectual assets, either in the form of explicit knowledge held in artefacts or as tacit knowledge possessed by individuals or communities.
Malhotra (1998)	KM caters to the critical issues of organizational adaptation survival and competence in face of increasingly discontinuous processes that seek synergistic combination of data and the creative and innovative capacity of human beings.
Swan et al. (1999)	KM is about harnessing the social and intellectual capital of individuals in order to improve organizational learning capacity.
Beckman (1999)	KM is the formalization of and access to experience, knowledge and expertise that create new capabilities, enable superior performance, encourage innovation, and enhance customer value.
Laudon and Laudon (1999)	KM is the process of systematically and actively managing and leveraging the stores of knowledge in an organization.
Beijerse (1999)	KM is achieving organizational goals through the strategy-driven motivation and facilitation of knowledge workers to develop, enhance and use their capability to interpret data and information (by using available sources of information, experience, skills, culture, character, personality, and feelings, etc.) through a process of giving meaning to these data and information.
O'Dell et al. (2000)	KM is conscious strategy of putting both tacit and explicit knowledge into action by creating context, infrastructure, and learning cycles that enable people to find and use the collective knowledge of the enterprise.
Rumizen (2002)	KM is the systematic processes by which knowledge needed for an organization to succeed is created, captured, shared and leveraged.
Neilson (2008)	KM is a discipline that promotes an integrated approach to identifying, retrieving, evaluating, and sharing an enterprise's tacit and explicit knowledge assets to meet mission objectives. It is to connect those who know with those who need to know (know-why, know-what, know-who, and know-how) by leveraging knowledge transfer from one-to-many across the Global Army Enterprise.
First Army KM Doctrine (2008)	KM is the art of creating, organizing, applying, and transferring knowledge to facilitate situational understanding and decision making. KM supports improving organizational learning, innovation, and performance. KM processes ensure that knowledge products and services are relevant, accurate, timely, and useable to commanders and decision makers.
Frost (2010)	KM is to provide the right knowledge to the right people at the right time in the right context. http://www.knowledge-management-tools.net/

2.1.3 The Evolution of KM

Tracing back the origin of KM, it is generally considered that KM has gone through three major generations focusing different aspects (Snowden, 2002; Koenig, 2002; Vorakulpipat et al., 2006; Dixon, 2010; Rezgui et al., 2010). KM pioneers state that the first generation of KM focuses heavily on documents: leveraging explicit knowledge by building knowledge repositories or expert systems; the second generation of KM tends to promote tacit-explicit knowledge conversion and focuses more on people and experience; and the third generation of KM focuses on the complex system of collective interactions, organizational learning and innovation capacities (Snowden, 2002; Dixon, 2010). Figure 2-1 and Table 2-3 summarize the evolution and characteristics of the three generations of KM.

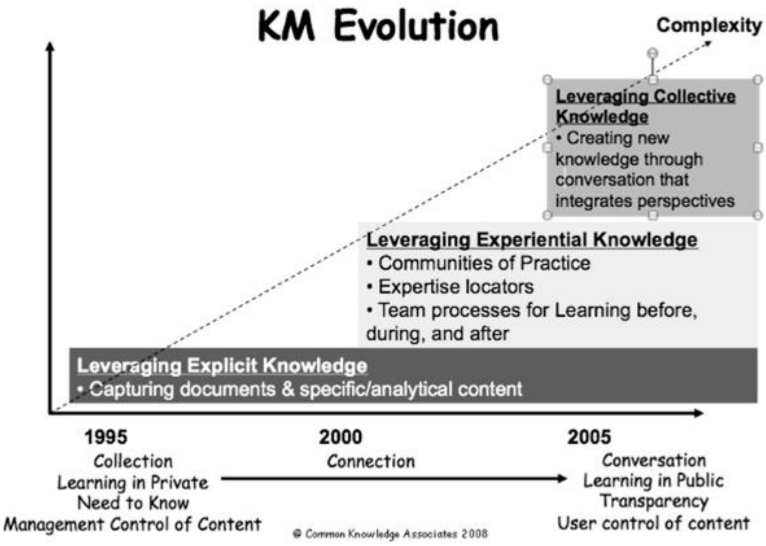

Figure 2-1 Overview of KM Evolution (Dixon, 2010)

Table 2-3 The KM Evolution
(http://i-p-k.co.za/wordpress/allowing-human-ingenuity-to-unfold/a-conceptual-framework-of-the-evolution-of-knowledge-management/)

1st Generation: (Document-based KM)	2nd Generation: (People-based KM)	3rd Generation: (System-based KM)
Aggregated, organized and analyzed information and data	Skill of using knowledge to create something unique	Complex phenomenon emerging from s social system (beyond the sum of individuals)
Stored in documents or data warehouses	Stored in human brains	Stored in systemic interaction and relations
Extract, capture, store and disseminate information	Interact, share and exchange knowledge	Co-create, discover and transform sense & meaning
Made available through search and retrieval	Made available in human interactions	Made available by understanding the whole through conversation and creating sense & meaning
Human beings are reluctant to share their knowledge	Human being are eager to promote their expertise	Human being depend on interaction to be knowledge
Produce & Provide information for rational management	Share & learn for improvement and effectiveness	Understand & innovate for sense-making and impact

2.1.4 KM Current Challenges and Key Issues

Firstly, it is recognized that the dramatic changes in working patterns have introduced great challenges and constraints to the contemporary KM practices. Nature of work in organizations changes from simple, routine, and individual work to complex, emergent, and collaborative work (Nonaka & Toyama, 2005). Not long ago, hierarchies and structures were clear and of utmost importance at workplace. The work handling procedures were well informed and the problem solving paths were seemingly obvious. The work processes and work flows were well defined and documented. The knowledge required for problem solving was known and straight-forward. Oppositely, knowledge work cannot be easily described and defined in a simple or static flow chart or process diagram any more. The knowledge created at workplace grows immense, and shared with others through complex social network. Knowledge workers are required to be fast learners and act strategically in order to keep up the performance and social position. The implication of such trend is that organizations are no longer mechanistic entities but networks of complex and interdependent communities towards an organic development. However, conventional approaches are no longer capable in helping administrative policy-makers making KM strategies that work. The challenges fall on the resolution of dealing with the complex nature of the new generation of KM, e.g. non-linear causality, emergence, feedback loops, uncertainty, etc. How to gain a whole picture of what is happening in the office, how to understand phenomena and harness the complexity in a good way that favors the organization becomes a key issue in the new agenda of the future KM. Although better management of knowledge could bring along great benefit, many KM programs have failed. The Chief Knowledge Officer (CKO) at international management and technology consulting firm Booz-Allen and Hamilton has suggested that up to 84 % of all knowledge management programs fail (Philip, 2003). According to Hylton (2002a, 2002b), the reason why KM initiatives go wrong is the failure to identify the knowledge needs, inability to clearly grasp the whole system, or the effectiveness of KM initiatives only can be analyzed in hindsight.

Secondly, a lot of KM initiatives fail because of the ignorance of the human behaviors. For example, how individual allocate effort on either creating new knowledge or sharing knowledge from time to time, will most people hold cognitive bias towards some certain choice, will it always work for promoting high connectivity among knowledge workers and encourage no barriers for knowledge sharing, how little change in microscopic individual decision making on pursuing certain KM strategy affect the organizational outcome? These factors are critical as well. Unfortunately, the behavior-oriented KM is still missing in the literature and conventional approaches concerning individual behavioral decision-making are mostly qualitative and content-oriented, since the purpose is more on eliciting tacit experience. Failing to consider the individual and collective decision-making behavior on KM, the evaluation of KM policy effectiveness will highly unlikely be successful.

Thirdly, difficulty in gasping the whole picture of the organization in a holistic manner is indeed implying that there is a missing link between microscopic and macroscopic level. Conventional KM approaches briefly mentioned in the KM evolution seldom consider this micro-macro links. There are three major reasons: (1) no system thinking: problem or deficiencies are still treated as parts and micro-macro link is neglected; (2) any conventional KM initiatives when implemented, it takes a long time to see the effectiveness, hence, only short term benefit is valued; (3) some academic scholars using conventional KM approaches tend to avoid micro-macro link on purpose because it is always criticized that one cannot compare KM efforts with organizational performance directly since environmental factors cannot be ignored and its effect on the organizational performance is unknown and unquantifiable.

In summary, the limitations of handling non-linear causality, unknown agent's behaviors, growing complexity, uncertain environment, and the lack of a micro-macro links suggest an incommensurability (Kuhn, 1962) which will lead to a paradigm shift. New set of theories, methodologies, and practices is needed in coping with KM Complexity.

2.2 Towards a Transdisciplinary KM

2.2.1 KM on Complexity Theory

Further enriching the third generation of KM as system oriented era of KM development, Snowden (2002) suggests that complex adaptive system theory is needed to create models that utilize self-organizing capabilities of the informal communities and identifies natural flow of knowledge creation, disruptive, and utilization because linear cause and effect are rarely found among knowledge exchange activities in organizations any more. Thus, a new paradigm of complexity has emerged. It would be inadequate or even dangerous if we still use our old way of linear thinking in KM. A pioneer education scholar Jörg argues that complexity theory may be helpful for us to escape the old ideas and the blind spots of social sciences and system science and to build up a new science – a science which may be of help of deal with the complexity of reality as we may view it and experience it in the very practice of knowledge interaction (Jörg, 2004).

Complexity science is a fundamentally new way of looking at physical, biological, and social phenomena. It is a cross-disciplinary field with its own approach to knowledge creation, sharing and learning capability. Complexity science spans scales from particle fields to information mechanics (physical analysis of the dynamics of information transmission) and adaptive systems (learning and consciousness, including neural systems), to human society, ecosystems and extraterrestrial space. In the literature, there is relatively little work on developing complex social systems theory than complex natural systems. Mitleton-Kelly (2003) stated ten principles of complexity and highlighted the generic characteristics of complex adaptive systems which include emergence, connectivity, interdependence, and feedback (Figure 2-2) This work offers an overview of the key indicators that can make complex system more understandable and describable.

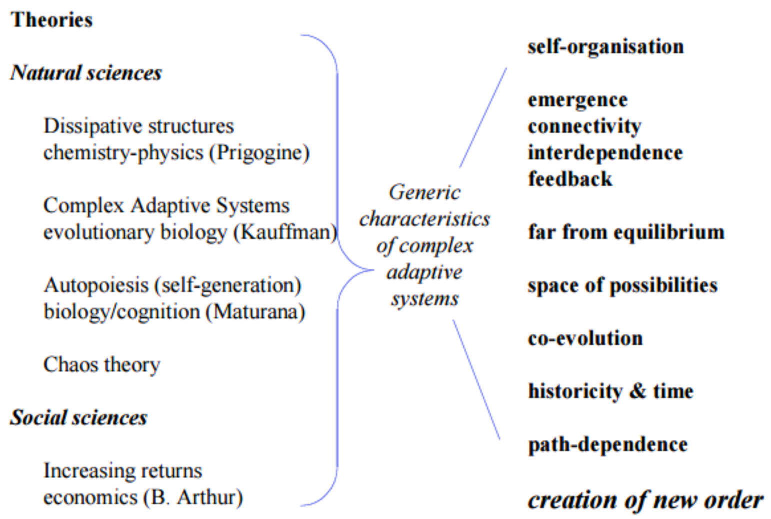

Figure 2-2 Principles of Complexity

Complexity science is the study of complex systems which is a system having multiple interacting components, of which the overall behavior cannot be inferred simply from the behavior of components. The computational modeling and simulation methodology is considered appropriate to deal with complexity issue of social phenomena for a large variety of reasons. First of all, it is widely recognized that the non-linear dynamics of a system are not mathematically tractable; whereas simulation is highly advantageous; Second, there is a desire to grow the system and create emergence from the bottom-up without introducing perturbation to the system; Third, computational analysis is particularly suitable for exploration of short-term and long-term phenomena. Finally, there is growing concerns about issues related to scalability which conventional methods are incapable, whereas simulation renders the ability to handle scalability. In addition to deduction and induction, simulation is sometimes seen as a third methodology for doing research. Even though simulation does not prove theorems, it can enhance our understanding of complex phenomena that have been out of reach for deductive theory.

Agent-based modeling (ABM) is a new analytical and computational method for social sciences that allows one to create, analyze, and experiment with, artificial worlds populated by agents and permits them to study how rules of microscopic agents' behavior give rise to the macroscopic regularities and organizations (Epstein and Axtell 1996; Axelrod 1997; Epstein 1999; Axtell 2000; Gilbert, 2008b). ABM is a kind of microscale model (Gustaffsson and Sternad, 2010) that is used in simulating the simultaneous operations and interactions of multiple agents in an attempt to re-create and predict the appearance of complex phenomena. ABM offers the possibility of modeling individual heterogeneity, representing explicitly agents' adaptive rules for decision-making, generating social interaction and evolution, and situating agents in a geographical or another type of space (Gilbert, 2008a). Its favorable features include modularity, great flexibility, large expressiveness and possibility to execute in a parallelized way (Taber and Timpone, 1996). It is particularly suitable for topics like decentralized decision making, self-organization, emergence, local-global interactions, and heterogeneity in a simulated system (Bandini et al, 2009) where macro phenomena are usually irreducible or fathomable. The characteristics of ABM include focusing on bottom-up autonomous interactions instead of top-down control, featuring a large number of heterogeneous agents instead of identical or dissimilar actors; assuming the environment is constantly changing and evolving instead of a fixed one; studying dynamics and transient trajectories far from equilibrium instead of studying equilibriums. Most ABMs consist of: (1) numerous agents specified at various scales; (2) decision-making heuristics; (3) learning rules or adaptive processes; (4) an interaction topology; and (5) a non-agent environment. Therefore, it fits to the niche when simulating an organization as a complex adaptive system and examining the KM evolution are desired. Nevertheless, there are notable limitations on ABM, such as the validity of the modeled human behavior, the difficulties in reasonable parameter calibration and model self-validation, etc.

2.2.2 KM on Behavior Economics Theory

Personal knowledge management (PKM) was introduced in 1999 which refers to the management of knowledge at the individual level (Wright, 2005). However, the seminal work mainly studies processes that a person manages his/her knowledge in daily operation (Grundspenkis, 2007) and provides support to enhance individual growth and learning. Behavioral decision-making on KM processes, social learning preference, or other cognitive related factors have not yet been focused. The PKM is a bottom-up approach, however, it does not establish a micro-macro link, and therefore, how individual management knowledge that creates organizational value is still unknown. The current practice is still considered to be far behind and inadequate.

On the contrary, this study aims at unfolding the bounded rationality, behavioral decision-making on KM effort, social preferences and influences, and other factors at microscopic level. To be specific, how individuals behaviorally adjust the likelihood of choosing KM strategies throughout timespan and what KM policies lead to optimized collective performance considering the human nature are of primary concerns. Since Simon's (1955) early work, evidence has shown that human decision making often falls short of the purely rational model (Haley and Stumpf, 1989). Instead of achieving rational decision making, they figure out efficient rules or mental shortcut to form judgements can choices. On contrary with rational choice theory, other models focus on heuristics and cognitive biases (Kahneman et al., 1982; Schwenk 1988; Stevenson et al., 1990). Commonly, when people come across complex problem with limited knowledge and time, the application of biases and heuristics yields satisficing results to problems for agents in an effective and efficient manner. Many public policies and commercial policies without considering the behavioral reaction of the collection of people are doomed to fail.

Behavioral economics investigates the effects of psychological, social, cognitive, and emotional factors on the economic decisions of individuals and institution and examines what results and consequences, such as returns and resources, will be realized. This field of study on the contrary with classic economics, is mainly concerned with bounded rationality of economic agents. It also is considered as a trans-discipline that combines psychology, neuroscience, and microeconomics theory. Designing and applying experiments with human subjects are common approaches for behavioral economists to study human behaviors since they help research understand how and why the economic agents or the social systems behave so.

2.2.3 KM on Micro-Macro Link Theory

Macrosociology studies large-scale phenomena whereas microsociology attends to smaller-scale phenomena. Macrosociology and microsociology have developed almost independently of one another. For long, the issue of how to link these disparate levels of analysis, how to close what is often termed the "micro-macro gap", has been debated within theoretical sociology (Turner & Markovsky, 2007). Intuitively, it is relatively easy to bridge microscopic and macroscopic levels. However, it is indeed difficult to derive formal theories about micro-macro link or even construct conceptual framework clearly since the micro-macro gap is vague and two levels are influencing each other all the time. ABM has the advantage in bridging the micro-macro links and unfolding the black box non-linear causality due to its generative nature. If microscopic specifications are theoretically plausible, the model is based on solid empirical ground. If the simulation results are robust against simulation parameters, then the microscopic specifications are accepted to satisfy the criterion of "generative sufficiency". ABM uses presuppose rules of behavior, allowing the effect of micromotive to be amplified into macrobehaviors. Agents' local effort and decision-making can grow the collective outcomes through social networks and interactions. It also covers various exogenous or endogenous conditions that may alter the macroscopic outcomes. It consciously grows the collective system and creates emergent patterns of behaviors. Overall, both qualitative and quantitative results can be produced. Hence, it is regarded as a possible and advantageous choice.

2.3 Towards an Integrated KM

Through reviewing the relevant literature, an integrated KM approach is proposed as the possible solution to cope with complexity and overcome the limitation of the conventional approaches. The integrated approach composes of an agent-based simulation and a series of behavioral experiments with human participants. The ABM and behavioral experiments indeed are mutually beneficial to each other (Figure 2-3). There are notable limitations on applying ABM alone, such as the validity of the modeled human behavior, the difficulties in reasonable parameter calibration and model self-validation, etc. These limitations can be overcome by behavioral experiments. On one hand, in the physical science of complexity, difficulties are usually overcome by controlled experiments. On the other hand, in social science, the utilization of controlled behavioral experiments can also be applicable. Indeed, controlled behavioral experimentation is largely employed in psychology and socio-economics to understand human behaviors, strategic decision-makings, interactive learning and social preferences. It also should be a powerful methodology in KM organizational studies. However, to produce statistically meaningful results, millions of repetitions of experiments are required which can be extremely resources and time consuming; additionally, many influential variables of human traits are not feasibly to be controlled, e.g. preferences, freewill and optimistic or pessimistic mood, which may lead to systemic errors. While in the simulation, these experiment constraints can be easily eliminated. Therefore, it is argued that the only solution is the integration of agent-based simulation and behavioral experiments.

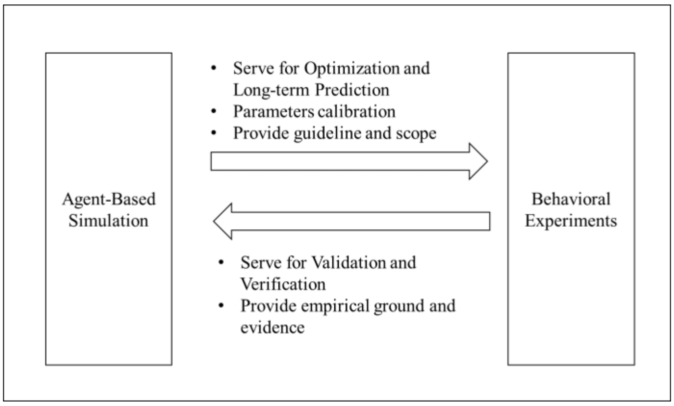

Figure 2-3 ABM Simulation and Behavioral Experiments Relationship

CHAPTER 3 RESEARCH ROADMAP

This chapter firstly presents the establishment of the research roadmap for achieving the objectives mentioned in the Chapter 1; secondly it articulates the design rationale of a basic KM game and an extended KM game which are regarded as abstract or toy models of complex organizational KM reality; thirdly it argues the inevitable choice of integrating ABM with behavioral experiments; lastly it explains the relationships between the basic KM game and the extended KM game.

3.1 Research Roadmap

In order to achieve the primary, additional, and ultimate goals mentioned in Chapter 1. A holistic research roadmap is depicted in Figure 3-1. In this study, organizational KM is considered as a complex adaptive system whose value creation is driven by member agents' KM effort from the bottom-up. Similar with many well-established fields of study, e.g. Physics, Biology, or Economics, "toy models" or "abstract models" of the complex mechanism in the reality are often employed to address questions of interest. In this study, a basic KM game concerning the environmental uncertainty and an extended KM game concerning the inventive system and social interactions are developed as toy models representing the organizational KM reality. Two games are targeting different aspects of the organization KM, hence some unnecessary features are turned off/isolated, for example, in the basic KM game, incentive system is excluded, whereas in the extended KM game, environmental conditions are turned off. Both games serve the purpose to understand the microscopic KM effort impact on the macroscopic outcomes and explore administrative interventions and their effectiveness.

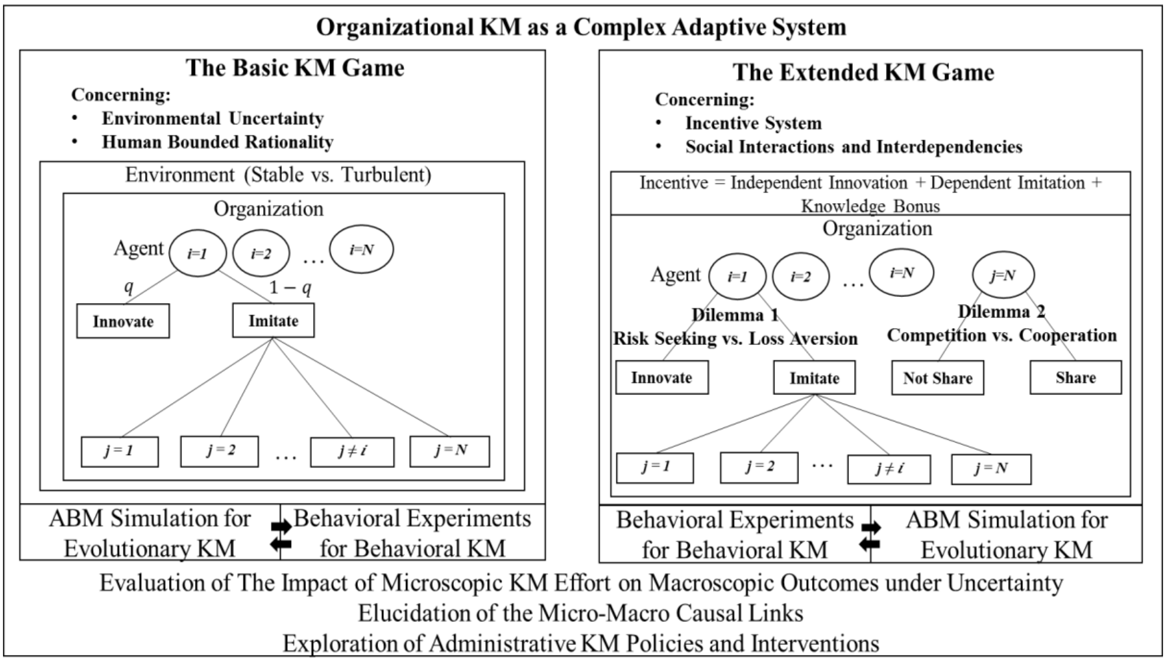

Figure 3-1 Research Roadmap

3.2 The Abstract or Toy Models

The design rationale behind simplifying the organizational KM reality into two KM games is for better understand the causal relationships, interaction mechanism, and micro-macro links. The proposed games are considered as abstract or toy models that contain the ingredients that are necessary to address the questions of my research interest. An abstract/toy model abstracts the reality into a set of elements that essentially related to understand a particular mechanism. There are plenty of great examples of abstract/toy model that have largely enhanced our understanding of physical, biology, or economical world, such as the Ising model for understanding ferromagnetism and phase transition, cellular automata for studying pattern formation, prisoner dilemma and minority game for building game theory, and so on. The advantages of abstract/toy models include: for better elucidate complex causal mechanism, it allows *isolation*, in other words, irrelevant variables are excluded while only essential elements are retained; it is easy to manipulate and observe and it offers you the data that serves your purpose; and it is feasible to be conducted in laboratories and cost-effective in execution. There are always critiques about how abstract the model is regarded as appropriate and how much validity it can claim if it is simplified. The proposed KM games do not aim at establishing a sophisticated one that serves general purpose and fully clone the reality, instead, they keep the necessary elements as minimum and as a conceptual representation of some phenomena. That is to say, someone else's KM model addressing different issues may be essentially different. Only selecting two key KM processes – knowledge creation and sharing cannot claim to be the standard or anything fully realistic, because there are numerous other processes, but they are two essential processes without which there is no KM at all. The principle upheld in this study is to keep models as simple as possible particularly for the questions of interest of this study only.

3.3 Integrated KM Methodology

Evolutionary and behavioral KM are of great interest in this study. Hence, the ABM simulation and behavioral experiments are considered as desired options for methodological consideration. However, either method has limitations by applying alone. On one hand, the pros of ABM simulation are that it is good for optimization, long-term prediction, as well as rules or parameters calibration which are not feasible by behavioral experiments. The cons of ABM simulation include that it lacks of an empirical ground for the validity and accuracy of behavior rules and parameter settings specified in the model. On the other hand, the pros of behavioral experiments include that the rich empirical observation and solid ground data can be gained, whereas the cons of behavioral experiments include that to produce statistically meaningful results, millions of repetitions are needed, in addition, many influential variables of human related traits are not feasibly controlled, for instance, social preferences, freewill, or mood, etc., which may cause systemic errors. Through ABM simulation, rough insights can be gained quickly, specific problem of large social system can be narrow down into concrete themes, and scope of the study can be decided easily. Hence, through integration, ABM and behavioral experiments complement each other. ABM serves as a guideline for behavioral experiments and expands the study capacity into larger scale and longer time for optimization, while behavioral experiments provide empirical ground and evidence to ABM. Therefore, the integrated approach is considered as an inevitable and highly advantageous choice.

3.4 The Relationship between The Basic and Extended KM Games

The basic KM game and the extended KM game center different study themes and interaction mechanisms. The basic KM game attempts to unfold the impact of environmental uncertainty on microscopic agents' behavior and macroscopic organizational outcomes in the long run and reveal the human endogenous decision behaviors guided by bounded rationality at microscopic level when administrator implement exogenous KM policies. The extended KM game induces an administrative incentive system at macroscopic level with monetary reward and knowledge bonus to study the microscopic adaptive learning and social interactions of agents. The basic KM game targets more on system conditions and microscopic reasoning while the extended KM game focuses more on incentive stimulation at macroscopic level and social interactions and social interdependency at microscopic level. Both games are independent and self-contained investigations, meanwhile, they are complementing to each other for better understanding the micro-macro links of the organizational KM and conditions that facilitate or inhibit optimization.

CHAPTER 4 THE BASIC KM GAME

This chapter explains the basic KM game in details, in terms of the design of conceptual framework, the implementation, data gathering and analysis, and results comparison, etc. Firstly, the conceptual framework is presented; secondly, the game is elaborated again in ODD protocol which is considered as a well-recognized tool for model description and communication; thirdly, the basic KM game is implemented in both agent-based simulation and behavioral experiments. Data is generated in simulation and collected in the experiments. Both results are analyzed and compared. With empirical evidence gained from the experiments, agent-based model improvement is proposed and tested. The findings of the basic KM game are summarized at the end of this chapter.

4.1 Conceptual Framework

The basic KM game aims to study the evolutionary KM by agent-based simulation and the behavioral KM by behavioral experiments with human participants. Inspired by the knowledge diffusion through social network model developed by Chang & Harrington (2005), a conceptual framework of the basic KM game is designed and illustrated in Figure 4-1.

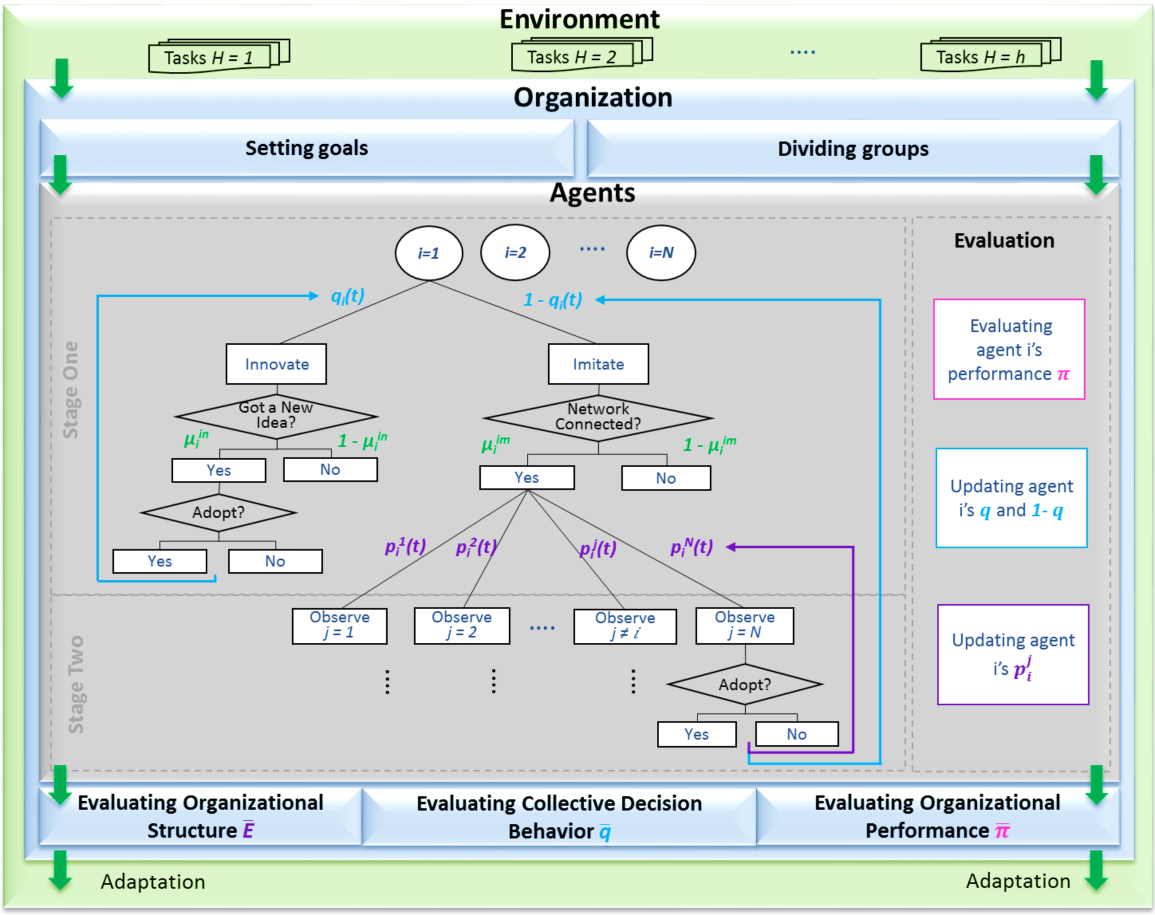

Figure 4-1 The Conceptual Framework of The Basic KM Game

Overall, the organizational KM is considered as a complex adaptive system. The game contains three entities, namely the agent, the organization, and the task environment. Agent's KM decision-making involves two stages: choosing KM strategy: innovation with an endogenous probability $q_i(t)$ or imitation with an endogenous probability $1 - q_i(t)$ and choosing other people with an endogenous probability $p_i^j(t)$. Knowledge creation and knowledge sharing are two essential processes on the problem-solving perspective (Nickerson and Zenger, 2004). Since the KM game will be implemented in behavioral experiment and played by human participants, for easy explanation and understanding purpose, knowledge creation is labeled with innovation, and acquiring shared knowledge or knowledge sharing is labeled with imitation. This design claims no standard or accuracy of how KM should be. Indeed, there is no universal agreement on how KM, innovation, or imitation are precisely defined. It is the abstraction and isolation that are needed in the process of scientific modeling and are simple enough to serve the purpose of this study. There are two exogenous factors representing administrative KM policies at macroscopic level that are controlled by the policy maker for optimization purpose, namely the productivity of new knowledge with an exogenous probability μ_i^{in} and the connectivity of the social network with an exogenous probability μ_i^{im}. The purposes are to enable the feedback loops or the micro-macro links, explore how exogenous KM policies affect endogenous individual decision-making behaviors, and identify what organizational outcomes are generated from the bottom-up under such conditions. Organizational decision behavior $\bar{q}$, emergent structure $\bar{E}$, and organizational performance $\bar{\pi}$ are measurements to evaluate the organizational outcomes on macroscopic level.

4.2 The ODD Protocol

Design and Framework – The ODD Protocol

ODD stands for Overview, Design concept, and Details. The ODD Protocol is one well-known tool to help researchers formulate and describe the ABM in a standardized and structuralized manner. It is developed by a large group of experienced researchers to create factual, complete, quick, easy, and consistent model descriptions (Grimm et al. 2006; Railsback and Grimm, 2011). Although the proposed KM games developed in this study not only include an ABM but also behavioral experiments, it is still a good choice to use The ODD Protocol, since there are plenty of advantages of using ODD, for example, it helps researchers put scattered thoughts into a hierarchical roadmap and forces them to think further in a more detailed and concrete way; it explicitly communicates to the readers with all the information so the developed work can be re-implemented, replicated, and reproduced; and it provides a generic language that makes the complex model more intuitively understandable. Moreover, it is now rapidly gaining wide acceptance in the social science literature (Polhill et al., 2008). Therefore, the basic KM game and the extended KM game will be presented in the ODD format (Figure 4-2).

Elements of the Updated ODD Protocol		
Overview	1. Purpose	
	2. Entities, state variables, and scales	
	3. Process overview and scheduling	
Design Concepts	4. Basic Principles	
	● Emergence	
	● Adaptation	
	● Objectives	
	● Learning	
	● Prediction	
	● Sensing	
	● Interaction	
	● Stochasticity	
	● Collectiveness	
	● Observation	
Details	5. Initialization	
	6. Input Data	
	7. Submodels	

Figure 4-2 The ODD Protocol (Grimm et al., 2006)

Overview – Purpose

The purpose of the basic KM game is to study the adaptive behavior of knowledge workers' KM effort at microscopic level and the impact on organizational outcomes at macroscopic level; and to elucidate the causal relations among exogenous KM policies, endogenous decision adjustment, environmental uncertainties, and human bounded rationality.

Overview – Entities, State Variables, and Scale

There are three entities namely The Agent, The Organization, and The Environment. Agents reside in the organization that are characterized by groups they belong to, tasks for problem solving, KM strategies, probabilities of choosing the strategies, social network for searching other agents, probabilities of choosing other agents, adaptive learning ability, individual performance, and free will to choose strategies and people. The organization is characterized by administrative functions namely setting goal scope and dividing agents into groups, exogenous KM policies, collective decision behavior, emergent structure, and collective performance. The environment is characterized by the dynamic and uncertain problems to be solved by agents as tasks. In other words, the organization contains N individuals and adapts to its environment through KM effort. Each individual $i \in \{1, 2, \ldots, N\}$ faces H tasks. Corresponding to each task, there is a goal $\hat{\boldsymbol{s}}_i(t)$ that may change from period t to period $t+1$, indicating the dynamics of the task environment. Goals may also be different among individuals, implying the diversity of tasks for each individual.

Overview – Process Overview and Scheduling

At each period t, each agent needs to receive a task assigned to them by the organization, they need to choose either to innovate or imitation, if the new knowledge helps them improve individual performance, the probability of choosing the same KM strategy and the same knowledge worker (if imitation is chosen) will be updated, following that the organizational decision behavior, structure concentration, and collective performance measure will be evaluated and updated.

Design Concepts – Emergence

The organizational decision behavior, organizational structure, and the collective performance are emerged from the bottom-up based on agents' KM effort and social interactions.

Design Concepts – Adaptation

Period by period, agents make adaptive decisions on choosing KM strategies and choosing other agents who share out their knowledge to improve the individual performance. Hence, the collective individuals can move closer and closer to the environment and task goals. The organization based on different environmental conditions can search for optimized exogenous KM policies. However, this search is based on steady-state outcome comparisons, instead of dynamical search.

Design Concepts – Objectives

Agents are striking for better individual performance through their adaptive decisions on KM effort.

Design Concepts – Learning

Agents are learning from past actions. They will see at the end of each period, whether their chosen strategies improved their performance. If yes, they will increase the likelihood of the chosen ones again in the next period. If no, they will decrease the likelihood accordingly. The probability of choosing innovation $q_i(t)$ and imitation $1 - q_i(t)$, and the probability of choosing imitation target $p_i^j(t)$ are strategically adjusted overtime through agents' adaptive learning from time to time. They are endogenous decision behavior of agents on microscopic level.

Design Concepts – Prediction

Agents form a probability of choosing each KM strategy and each other agent. Through learning and adaptation, they constantly adjust these two probabilities. They make next decision based on such probabilistic predictions. Hence, the prediction is realized by probabilistic decision-making.

Design Concepts – Sensing

If agents successfully connect to the social network, they can sense other agents who belong to the same group and who belong to the different group. Hence, they can choose the agent strategically for social learning.

Design Concepts – Interaction

Agents when connect to the social network, they can sense and search for other agents. For example, when agent i choose, agent j, agent j's solution for agent i's chosen task will be shared. If agent i adopts the shared knowledge and improves individual performance, he/she will increase the probability of choosing agent j again in the future. The higher the chosen probability is the more likely agent i will interact with agent j.

Design Concepts – Stochasticity

There are two stochastic processes: one on assigning tasks for problem solving through KM, and the other on the dynamic movement of goals. When agent i chooses to innovate, a random task is assigned to him/her, under certain probability controlled by the administrator, he/she can create a new knowledge, and this new knowledge is randomly produced by the computer. Likewise, if agent i chooses to imitation, a random task is assigned to him/her, under certain probability controlled by the administrator, he/she can connect to the network and choose agent j, and agent j's solution is shared to agent i for solving the assigned task. For the dynamic environmental goal movements, as illustrated in Figure 4-3, firstly, the scope of organizational goal is decided with societal goal seed $\boldsymbol{U}$ as the center and R distance away as the radius of a circle – Organizational goal scope. Hence that $\Delta(\boldsymbol{U}, R)$ is the set of tasks for the organization; secondly, the whole population of individuals is divided into G groups which have independent goal scope with group goal seed g_k as the center and r distance away as the radius of a circle –group goal scope. This indicates that different individuals solve tasks in different domains. As individuals solving problems and moving closer to their goals, the goals are shifting as well. It is such a goal evolution that makes knowledge creation and diffusion vital. There are two key factors controlling the intensity of environmental turbulence, namely how often $(1-\sigma)$ and how far away ρ the goal shifts.

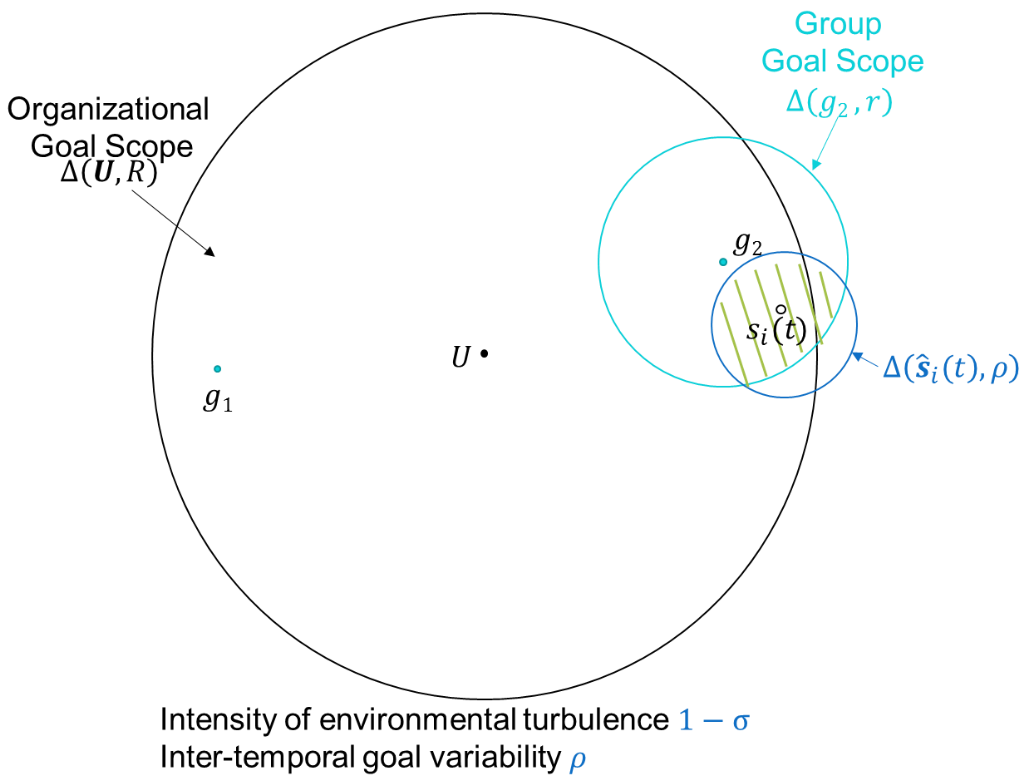

Figure 4-3 Dynamic Goal Movements of the Task Environment

Design Concepts – Collectiveness

In the organization, there are N agents assigned randomly to G groups. For agents in the same groups, their sets of goals to the tasks are similar, whereas agents in other groups, their sets of goals to the tasks are very different.

Design Concepts – Observation

All the data from period to period is recorded and stored in the database for further analysis. Data generated from the microscopic level includes agent's choice of KM strategy, choice of selected people for imitation, succeed or failed, individual performance, adjustment of decision-making probabilities, etc. Data emerged and to be observed at the macroscopic level includes collective decision behavior, organizational structured measured by entropy concentration, and collective performance.

Details – Initialization

At time zero, agents' existing solution sets, initial attractions to each KM strategy or other agent, the probability of choosing each KM strategy or other agent, assigning agents to groups, organizational goal scope, group goal scope, and agents goal sets are all initialized.

Details – Input Data

There is no additional input data or external sources used.

Details – Submodels

The microscopic agents KM effort is considered as the submodel. Agent's KM decision-making involves two stages: choosing KM strategy: innovation with an endogenous probability $q_i(t)$ or imitation with an endogenous probability $1 - q_i(t)$ and choosing other people with an endogenous probability $p_i^j(t)$. Knowledge creation and knowledge sharing are two essential processes on the problem-solving perspective (Nickerson and Zenger, 2004). There are two exogenous factors representing KM policies that are controlled by the policy maker for administrative intervention, namely the productivity of new knowledge with an exogenous probability μ_i^{in} and the connectivity of the social network with an exogenous probability μ_i^{im}. The purposes are to enable the feedback loops or the micro-macro links, explore how exogenous KM policies affect endogenous individual decision-making behaviors, and identify what organizational outcomes are generated from the bottom-up under such conditions.

4.3 Implementation in ABM

The pseudo code of the model is attached in Appendix I.

4.3.1 The Agent Model

There are N agents in a simulated organization. Each agent $i \in \{1, 2, \ldots, N\}$ holds H tasks for problem solving through KM effort. The solutions 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 solution choices available for each task. Denote $\boldsymbol{s}_i(t) \in \{0,1\}^{Hd}$, $\boldsymbol{s}_i(t) \equiv (\boldsymbol{s}_i{}^1(t), \ldots, \boldsymbol{s}_i{}^H(t))$ which is the vector of agents' solutions, and $\boldsymbol{s}_i^h(t) \equiv (s_i^{h,1}(t), \ldots, s_i^{h,d}(t)) \in \{0,1\}^d$ which is agent i's solution for task $h \in \{1, \ldots, H\}$. The heterogeneity of agents is represented by how different their solutions are to the same task. To quantify the degree of heterogeneity between two agents (i and j), the hamming distance is employed as the following:

$$D(\boldsymbol{s}_i, \boldsymbol{s}_j) \equiv \sum_{h=1}^{H} \sum_{k=1}^{d} \left| s_i^{h,k} - s_j^{h,k} \right| . \tag{1}$$

Corresponding to each task, there is a goal vector $\hat{\boldsymbol{s}}_i(t) \in \{0, 1\}^{Hd}$. Note that $\hat{\boldsymbol{s}}_i(t)$ may vary from period t to period $t+1$ indicating the uncertainty of the task environment. Goal vectors may also be different among agents, implying the diversity of tasks for different agents. The performance of agent i denotes $\pi_i(t)$ which is measured by the hamming distance between the goal and the solution.

$$\pi_i(t) = H \cdot d - D(\boldsymbol{s}_i(t), \hat{\boldsymbol{s}}_i(t)) \tag{2}$$

4.3.2 Two Microscopic KM Processes and Evolution

At each period t, a task is randomly assigned by the organization to each agent from the turbulent environment. Agent i has a chance to update his/her solution for moving closer to the goal (shortening the hamming distance) by either innovation or imitation. Denote μ_i^{in} as the innovation productivity of individuals, and μ_i^{im} as the connectivity of the social network. With probability μ_i^{in}, agent i can create a new knowledge, while with probability $1-\mu_i^{in}$, agent i fails or stays idle. With probability μ_i^{im}, agent i can connect to the social network and search other agents for social learning, while with probability $1-\mu_i^{im}$, agent i fails or stays idle. μ_i^{in} and μ_i^{im} are two exogenously specified parameters in the model as KM policies controlled by administrative decision-maker of the organization.

Assuming that agent i receives a goal vector $\hat{\boldsymbol{s}}_i(t)$ and has a current solution vector $\boldsymbol{s}_i(t)$, he/she can potentially obtain a new solution $\boldsymbol{s}_i'(t)$ by KM strategies - either innovation or imitation. Adoption or rejection of the created or learned new knowledge is determined by:

$$\boldsymbol{s}_i(t+1)=\begin{cases}\boldsymbol{s}_i'(t), & \text{if} \quad D\ (\boldsymbol{s}_i'(t),\ \hat{\boldsymbol{s}}_i(t))<D\ (\boldsymbol{s}_i(t),\ \hat{\boldsymbol{s}}_i(t)) \\ \boldsymbol{s}_i(t), & \text{if} \quad D\ (\boldsymbol{s}_i'(t),\ \hat{\boldsymbol{s}}_i(t))\geq D\ (\boldsymbol{s}_i(t),\ \hat{\boldsymbol{s}}_i(t))\end{cases}. \qquad (3)$$

If the new knowledge shortens the hamming distance between the agent i and the goal, it will be adopted. Meanwhile, the current solution held by the agent will be replaced by the new solution in the agent i's solution set. The KM strategy chosen will be considered successful. The likelihood of choosing the same KM strategy in the next period will increase. Otherwise, the new solution will be rejected. Meanwhile, the current solution held by the agent will not be replaced by the new solution in the agent i's solution set. The KM strategy chosen will be considered unsuccessful. The likelihood of choosing the same KM strategy in the next period of time will decrease. The evolution of adaptive KM decision-making is a two-stage process. The likelihood of innovation and imitation KM strategies is updated in Stage One while the likelihood of social learning targets is updated in Stage Two both by a version of experience-weighted attraction (EWA) (Camerer and Ho, 1999) learning rule. In Stage One, $q_i(t)$ denotes the probability that agent i chooses innovation while $1 - q_i(t)$ denotes the probability that agent i chooses imitation. Probability $q_i(t)$ is adjusted at each period on the basis of strategy attraction measures, $B_i^{in}(t)$ and $B_i^{im}(t)$, for innovation and imitation respectively. The evolution of $B_i^{in}(t)$ and $\mathrm{B}_\mathrm{i}^\mathrm{im}(t)$ is formulated as follows:

$$B_i^{in}(t+1) = \begin{cases} \phi B_i^{in}(t) + 1, & \text{if adopted} \\ \phi B_i^{in}(t), & \text{otherwise} \end{cases}, \tag{4}$$

$$B_i^{im}(t+1) = \begin{cases} \phi B_i^{im}(t) + 1, & \text{if adopted} \\ \phi B_i^{im}(t), & \text{otherwise} \end{cases}. \tag{5}$$

Therefore, if agent i chooses to innovate and then adopts the newly created solution, the attraction measure for innovation will increase by one unit after allowing the previous attraction level to decay by the factor $\phi \in (0.1]$. Similarly, the update of strategy attraction measure for imitation $B_i^{im}(t+1)$ applies in the same way. Given $B_i^{in}(t)$ and $B_i^{im}(t)$, the agent then updates the probability of choosing innovation as follows:

$$q_i(t) = \frac{(B_i^{in}(t))^{\lambda}}{(B_i^{in}(t))^{\lambda} + (B_i^{im}(t))^{\lambda}} \ , \tag{6}$$

with $\lambda > 0$ as the agent's sensitivity to attraction. In Stage Two, the people attractions and the probabilities are updated in the same way. Let $A_i^j(t)$ be agent j's attraction to agent i in period t. It evolves as follows:

$$A_i^j(t+1) = \begin{cases} \phi A_i^j(t) + 1, & \text{if adopted} \\ \phi A_i^j(t), & \text{otherwise} \end{cases}, \tag{7}$$

with $\forall i, \forall j \neq i$. Denote $p_i^j(t)$ as the probability that agent i is likely to imitate agent j, and it is adjusted each period on the basis of the attraction measures $\{A_i^j(t)\}_{j \neq i}$:

$$p_i^j(t) = \frac{(A_i^j(t))^{\lambda}}{\sum_{j \neq i}(A_i^j(t))^{\lambda}} \ , \tag{8}$$

where $\lambda > 0$ is the sensitivity to attraction. Endogenously derived $q_i(t)$ and $p_i^j(t)$, and exogenously given parameters μ_i^{in} and μ_i^{im} are crucial factors for understanding the KM behavior of the individual agents and the whole organization.

4.3.3 The Organization

The organization model controlled by administrative decision-maker has two functions, namely setting goals and dividing groups for the member agents, and evaluating the macroscopic outcomes, e.g. collective decision behavior, organizational performance and emerged structure.

Firstly, the scope of organizational goal is decided by setting the organizational goal seed vector $\boldsymbol{U}$. The organizational goal scope is controlled by R which is the maximum hamming distance to $\boldsymbol{U}$, so that $\Delta(\boldsymbol{U}, R)$ is the set of task vectors for the organization. As agents solving problems and moving closer to their goals, the goal vectors are shifting as well. It is such dynamic goal movements that make knowledge creation and diffusion vital. Secondly, in the organization, N agents are divided into G groups who have independent goal vectors determined by the organization initially, which means that different agents solve tasks in different domains. Let a_k be the set of agents belonging to group $k \in \{1,2,\dots,G\}$ and g_k be the seed vector used to generate the initial goal vectors for all agents,

$$\hat{\boldsymbol{s}}_i(0) \in \Delta(g_{k,}r) \quad , \forall i \in a_{\mathrm{k}}, \forall \mathrm{k} \in \{1,2,\dots,G\} \qquad (9)$$

where $\Delta(g_{k,}r)$ is a set whose "center" is $g_{k,}$, and r is the group goal scope. All agents in a_k then have goal vectors which lie within hamming distance r to the group seed vector g_k. The heterogeneity among groups is modeled by allowing a diversified set of group seed vectors. Since the organizational goal scope R is kept large enough while the group goal scope r is significantly small, agents in the same group would face similar tasks while agents in other groups would face different tasks. This is essential to the emergence of social structure in the organization.

The organizational model also includes the evaluation of the organizational decision-making behavior, collective performance, and the emergent organizational structure which are measured as follows:

$$\bar{q}(t) = \frac{1}{N}\sum_{i=1}^{N} q_i(t) \quad . \tag{10}$$

$$\bar{\pi}(t) = \frac{1}{N}\sum_{i=1}^{N} \pi_i(t) \quad . \tag{11}$$

Shannon's (1949) entropy $\bar{E}(t)$ is employed to measure the emergent structure. With the entropy for each agent defined as:

$$E_i(t) = -\sum_{\forall j \neq i} p_i^j(t) \cdot \log_2 p_i^j(t) \ , \tag{12}$$

the entropy for the whole organization can be calculated as follows:

$$\bar{E}(t) = \frac{1}{N}\sum_{i=1}^{N} E_i(t) \ . \tag{13}$$

Note that the larger the $\bar{E}$, the less concentrated the network is.

4.3.4 The Environment Model

The environmental uncertainty is modeled by a stochastic process of goal movements. In the period t, assume that agent i holds the current goal vector $\hat{\boldsymbol{s}}_i(t)$. In the period $t+1$, the goal remains unchanged under the probability σ, which stands for the stability of the environment, and shift under the probability $(1-\sigma)$, which stands for the intensity of turbulence in the environment. The shifting dynamics of the goal vector are guided by the following binomial process: The goal in period $t+1$, if different from $\hat{\boldsymbol{s}}_i(t)$, is chosen iid (independently with an identical distribution) from the set of points that lie both within hamming distance ρ from $\hat{\boldsymbol{s}}_i(t)$ and within hamming distance r from the original group seed vector g_k . Hence,

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

Note that ρ or less bits of the goal are randomly selected and flipped in the shifting process.

4.4 The Simulation

4.4.1 The Baseline Settings

The purpose of the baseline simulations is to lay a foundation for the further exploration on how macroscopic organizational outcomes are influenced by microscopic individual's decision-making, under the condition of the environmental turbulence and other factors. In the simulated organization, there are $N = 6$ agents equally and randomly assigned in $G = 2$ groups. For the baseline settings, $\mu_i^{in} = 0.5$ and $\mu_i^{im} = 0.5$ are deployed, so the efforts for agents to create a new knowledge by innovation or acquire a shared knowledge through social network are the same. The numerical values of other parameters and initial attractions are summarized in Table 4-1. Parameters μ_i^{in}, μ_i^{im}, ϕ, and λ govern an agent's decision-making behavior while R, r, ρ, and σ control the task environment. Initially, either innovation or imitation is equally preferred by the agents. For imitation, agent's attraction to any other agents at the beginning is neutral and not biased as well.

Table 4-1 Notations of Baseline Simulation Setting

Notation	**Definition**	**Baseline Value**
H	Number of tasks for each agent	12
d	Bits in each task/goal and solution	4
R	Organizational goal scope	16
r	Group goal scope	8
$1 - \sigma$	Intensity of environmental turbulence	0.25
ρ	Inter-temporal goal variability	2
ϕ	Attraction decay factor	0.99999
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

4.4.2 Simulation Sessions

To explore how the steady-state outcomes of the organization are caused by different exogenous innovation productivities and social network connectivity, a series of simulated experimentations are carried out with the parameter settings listed in Table 4-2. Simulation 1 and 2 are designed with relatively easy and difficult KM contexts to cross-check the results with the baseline neutral settings. Simulation 3 to 6 are performed to examine how organizational performance is influenced by the increasing connectivity of the social network, while the productivity of innovation is fixed low reflecting the fact that innovation is more difficult in the reality. The simulation is executed for 20 runs, each with the same duration ($t = 10{,}000$) and the same parameter settings, but initialized with different seeds for random numbers. To eliminate noise from the randomness in the initial conditions and goal shifting, results are averaged over all runs.

Table 4-2 Testing Various KM Policies in in Simulation

Simulation Sessions	**Innovation (μ_i^{in}) Productivity of New Solution**	**Imitation (μ_i^{im}) Connectivity of Social Network**
Baseline	0.5	0.5
S1	0.8	0.8
S2	0.25	0.25
S3	0.25	0.05
S4	0.25	0.3
S5	0.25	0.5
S6	0.25	0.8

4.4.3 Simulation Results

As shown in Figure 4-4 Baseline Collective Decision-making Behavior there is no significant difference in results among relatively easy, difficult and the baseline neutral KM contexts. For all three cases S1, S2 and Baseline, the endogenous organizational decision-making behavior $\bar{q}$ shows equal preference on either KM strategy since the exogenous policy (μ^{in}, μ^{im}) favors neither one; the organizational performance is greatly improved through agents' effort on creating new knowledge and sharing existing knowledge, then maximized and stabilized; Meanwhile, the organizational structure is emerged from the bottom-up and stabilized alongside the entropy decreases. For the relatively easy KM context ($\mu_i^{in} = 0.8, \mu_i^{im} = 0.8$), the structure is emerged faster and the structural pattern is clearer; whereas, for the relatively difficult KM context ($\mu_i^{in} =$

$0.25, \mu_i^{im} = 0.25$), the structure is emerged slower and the structural pattern is blurrier as can be confirmed through the time variation of entropy in Figure 4-6. For the baseline case, the time evolution of the averaged social attraction $p_i^j(t)$ is calculated and plotted in Figure 4-7, where the black diagonal grids indicate that agents do not learn from themselves, while the light grids indicate a strong social learning from agents listed on the horizontal axis to those on the vertical axis. The time change of the structural pattern indicates a strong intra-group learning than inter-group learning.

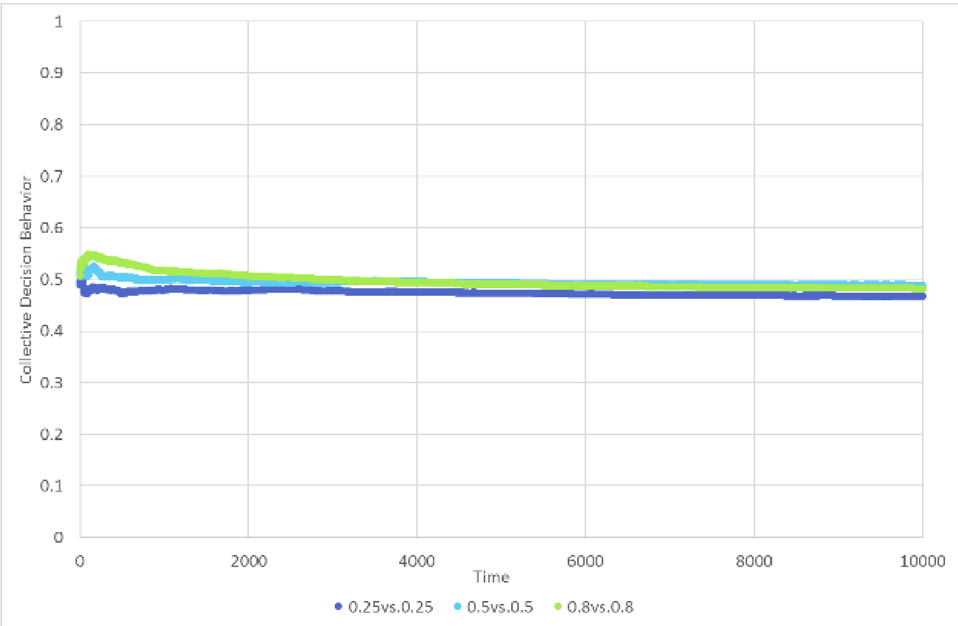

Figure 4-4 Baseline Collective Decision-making Behavior

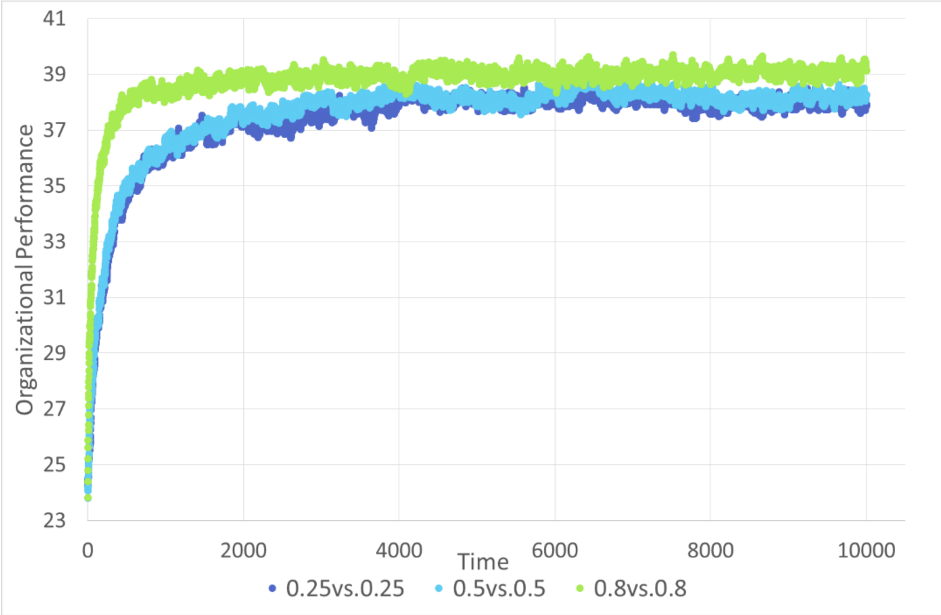

Figure 4-5 Organizational Performance.

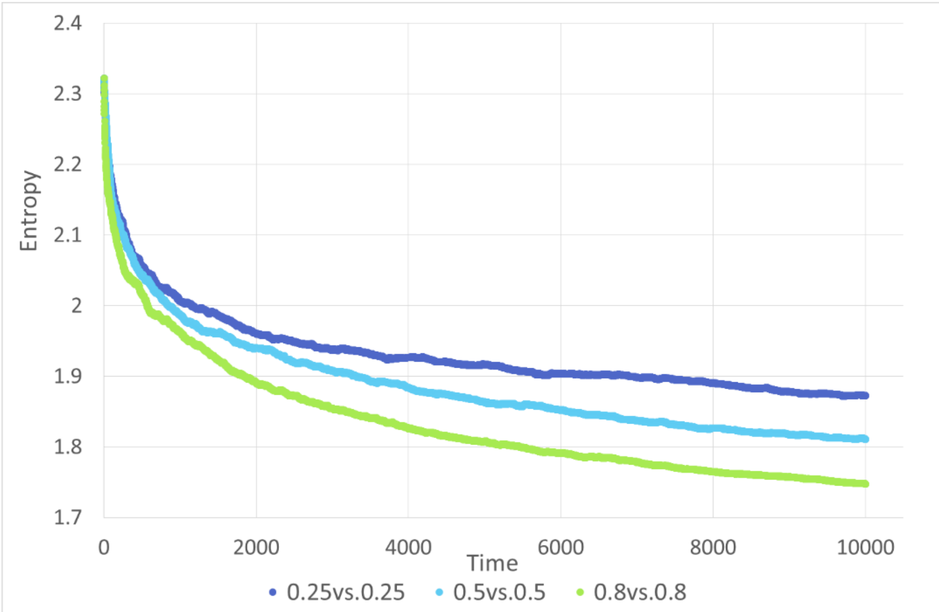

Figure 4-6 Entropy of Structure Formation

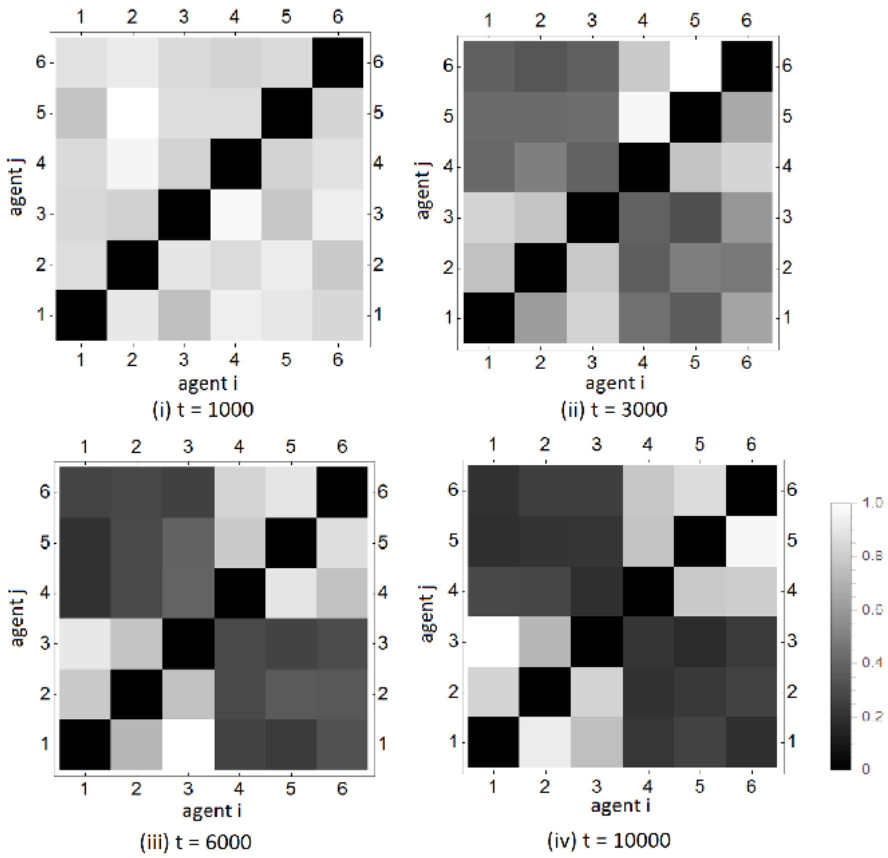

Figure 4-7 Intra-group learning vs. Inter-group learning of agents

One of the surprising findings from S3 to S6 shows a non-monotonicity in the steady-state organizational performance against the increase of social network connectivity. When the productivity of new knowledge μ_i^{in} is fixed low to 0.25, the connectivity of social networks is increased from 0.05, 0.3, 0.5 to 0.8. As shown in Figure 4-8 , the averaged steady-state organizational performances of the simulation sessions are not improved monotonically alongside the increment of network connectivity. Instead, it peaks at S5 then falls down at S6. In other words, a high connectivity of social network can be harmful to the organizational performance. In existing KM literature, knowledge sharing is always highly emphasized and encouraged (Maier, 2007). However, the significant finding here suggests that over sharing knowledge can be detrimental to the overall outcomes. The condition which causes such important phenomenon is articulated in the coming section. Note that standard deviations of organizational performance keep nearly constant as shown in error bars (less than 0.28), inferring that the discovered non-monotonicity is robust and reliable.

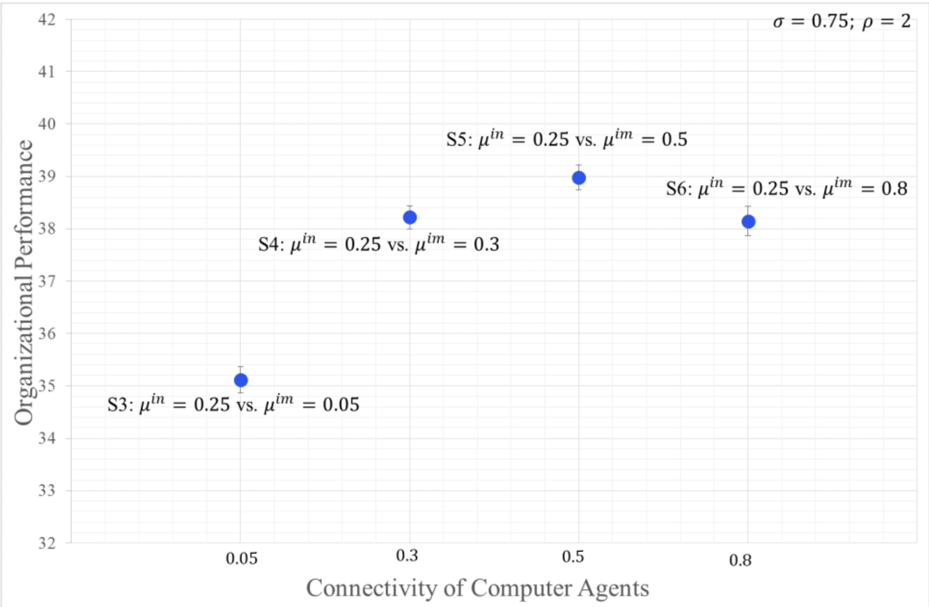

Figure 4-8 Non-Monotonicity of Organizational Performance in Simulation

4.5 Behavioral Experiments

4.5.1 The Computer-Aided Gaming Sessions

The purposes of the computer-aided behavioral experiments include verification of the developed agent-based model on the macroscopic organization level; observation of human behaviors in the reality for model improvement on the microscopic agent level; and identification of factors and conditions that may potentially and crucially influence the human decision-making and organizational outcomes. The experiment is designed as an online game challenged by human participants. A gaming software is developed in accordance with the same configurations and flows as those in the agent-based model shown in Figure 4-1. It is written in Java and has four modules including player interface, control panel, computational engine and database. Player interface allows participants to manage their accounts, utilize the real-time gaming information to form strategies, and experience a competition and cooperation environment. Screenshots of the game interface are shown in Figure 4-9. Like agents in ABM, each participant has to compete with one and another making KM efforts to gain the highest score. Control panel allows the game administrator to manipulate parameters, game rounds and information access rights. Computational engine is responsible for task allocation, hamming distance evaluation, player score calculation, and environmental turbulence generation. Lastly the database stores all the events and transactions for analysis.

Figure 4-9 Screenshots of the Gaming Software User Interface

Figure 4-10 Snapshots of the Behavioral Experiments

The gaming sessions are executed in the same settings with the simulation sessions except the one with relatively difficult KM context ($\mu_i^{in} = 0.25, \mu_i^{im} = 0.25$) because results would be unreliable in consideration of the possible frustrated emotional reactions of players. Thus, there are six gaming sessions played in total as shown in Table 4-3. Thirty-six graduate students coming from the Institute of Software, Chinese Academy of

Sciences participated in the experiment as volunteers. For one gaming session, six players are randomly divided into two groups. Figure 4-10 are selected snapshots of the behavioral experiments.

Table 4-3 Parameters Specified in Different Gaming Sessions

Gaming Sessions	**Innovation (μ_i^{in}) Productivity of New Solution**	**Imitation (μ_i^{im}) Connectivity of Social Network**
Game 1	0.8	0.8
Game 2	0.5	0.5
Game 3	0.25	0.05
Game 4	0.25	0.3
Game 5	0.25	0.5
Game 6	0.25	0.8

Since the timespan in the experiment is completely different from the simulation, deciding the number of rounds for each game is crucial. Several trial games were played for round number determination and game software testing. Finally, 80 rounds for Game 1 to 2 and 200 rounds for Game 3 to 6 are decided, since they are sufficient to reach the steady-state for evaluation and economically affordable in terms of time and manpower. Meanwhile, to shorten the individual searching and testing time when forming strategies, participants are informed with μ_i^{in} and μ_i^{im} in advance. They are also clear that players in the same group are assigned with similar tasks while players in the other group have far different ones. In other words, at the beginning of the game, participants understand that intra-group learning is more efficient than inter-group learning. In contrast, only through numerous iterations of reinforcement learning can such insight be realized by autonomous agents in the simulation.

4.5.2 Results of the Experiments

One result of gaming sessions, from the baseline Game 2, is shown in Figure 4-11. This indicates that along with participants' KM effort on innovation or imitation, the organizational performance is improved gradually, then it reaches a peak and stays stabilized. This progress qualitatively agrees with the simulation result but shows a much faster convergence to the steady state. This means that the pre-game briefing session with information on μ_i^{in} and μ_i^{im} and group task differences is necessary and effective. Different from the simulation, organizational performance in the steady state is lower and more fluctuated. The reason can possibly lie in low human engagement, poor learning efficiency, and fatigue. Heuristics rather than perfect rationality in decision making can also be the cause.

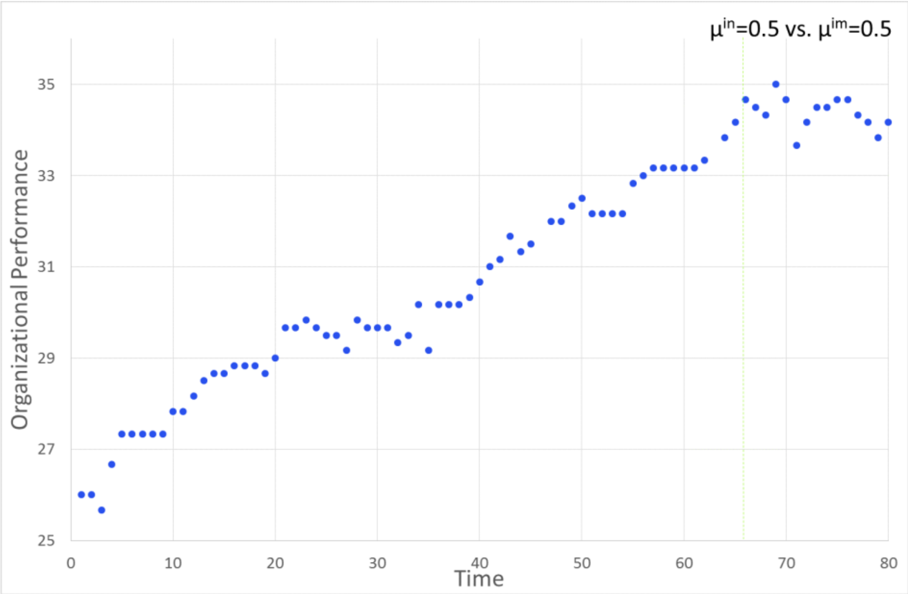

Figure 4-11 Organizational Performance in Game 2

At the steady state, the structural pattern is captured in Figure 4-12 for Game 2, revealing that players with similar goals hold higher tendency to learn among each other instead of reaching out for solutions in the other group. Bubble size indicates the frequency which players on horizontal axis choose players on vertical axis. The larger the bubble, the stronger the social learning is. Two distinct groups A and B can be identified. Although there is some noise caused by inter-group learning, the overall pattern matches the simulation results (Figure 4-7) well. The dynamics of structure emergence is illustrated in Figure 4-13 revealing the adaptation and adjustment of the inter-group learning and intra-group learning among agents.

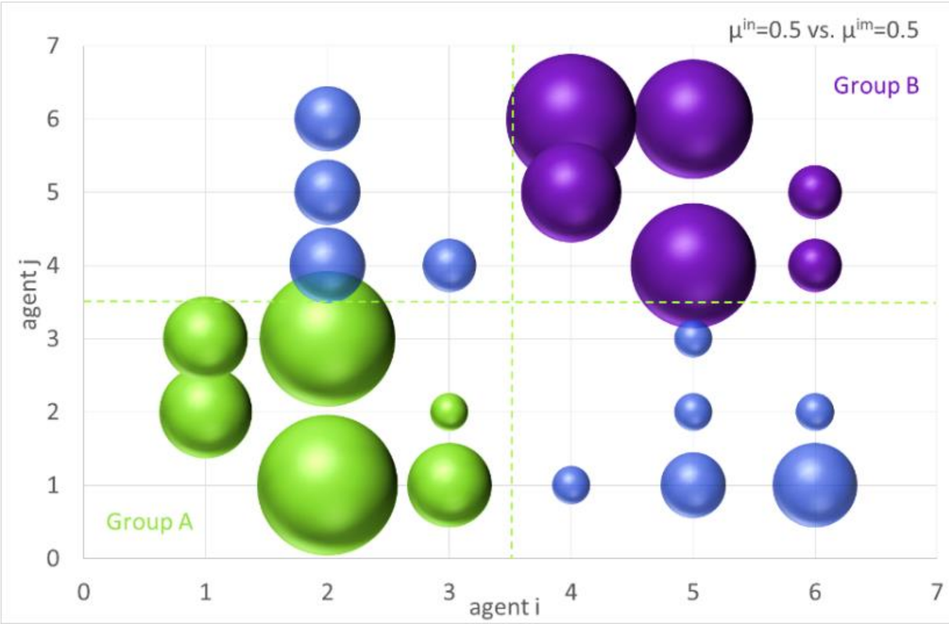

Figure 4-12 Emergent Social Structure and Social Learning

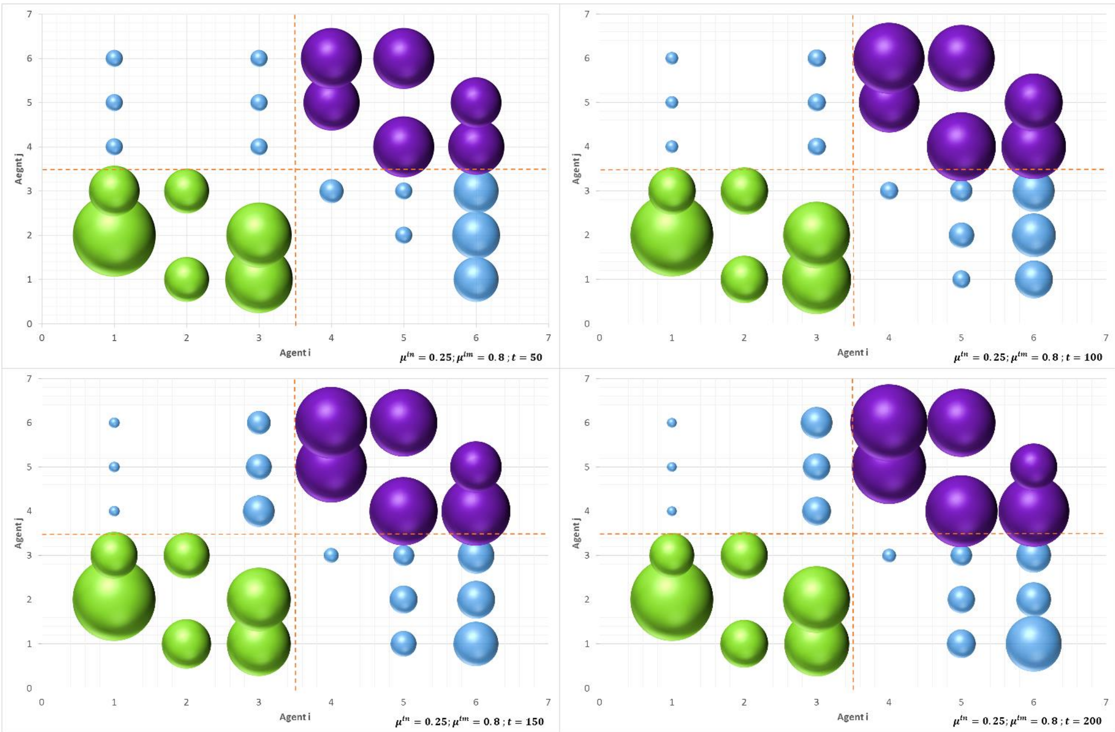

Figure 4-13 Dynamics of Structure Emergence

After the completion of G3 to G6, each long term steady-state organizational performance is calculated and plotted in Figure 4-14, showing a non-monotonicity as well, similar but stronger than the one in the simulation. With low innovation productivity, gradually increasing the connectivity of the social network can enhance the collective performance until a certain point, however, when further increased, it can be harmful to the organizational performance. Moreover, the noteworthy turning point ($\mu_i^{in} = 0.25, \mu_i^{im} = 0.5$) is in accordance with the simulation, except that standard deviations are larger.

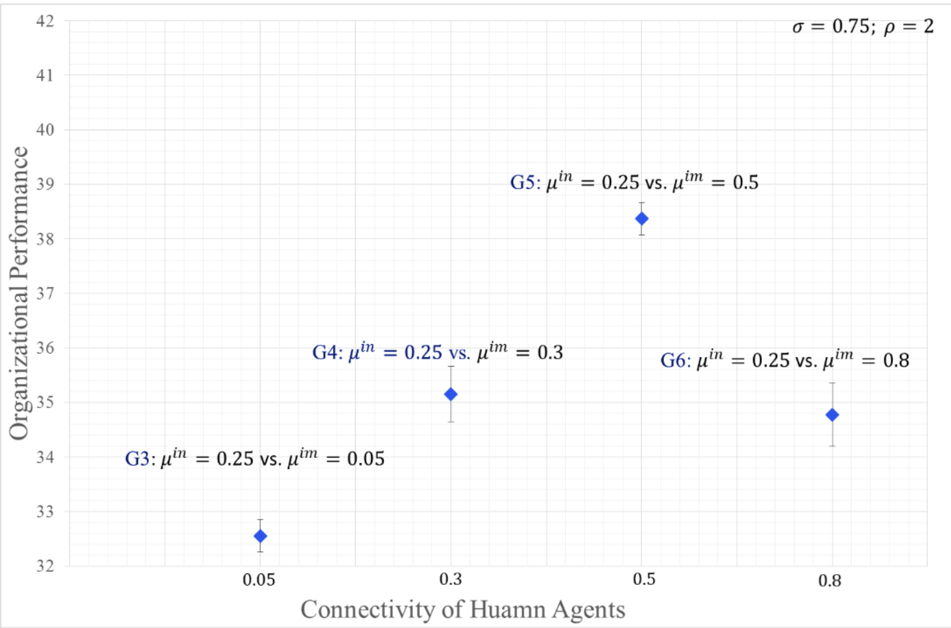

Figure 4-14 Non-Monotonicity of Organizational Performance in Experiments.

4.6 Results Comparison and Discussion

4.6.1 Results on Environmental Influences

Interestingly, results from both simulation and gaming sessions reveal non-monotonicity in organizational performance alongside social network connectivity increments. In other words, organizational performance is not enhanced and optimized by either innovation or imitation alone, but both. When the innovation productivity is fixed to $\mu_i^{in} = 0.25$, increasing social network connectivity as $\mu_i^{im} = 0.05$, $\mu_i^{im} = 0.3$, $\mu_i^{im} = 0.5, \mu_i^{im} = 0.8$ not always allows the organizational performance to continually strike. Both the simulation and the experiment reach a peak in the organizational performance at S5: $\mu_i^{in} = 0.25, \mu_i^{im} = 0.5$ and then a decline at S6: $\mu_i^{in} = 0.25$, $\mu_i^{im} = 0.8$. Now the question is why it happens. This phenomenon can be elaborated as the following: When social network connectivity is increasing, agents tend to engage more and more in social learning, sharing existing knowledge among one another, rather than creating new knowledge by innovation, since imitation is relatively easier than innovation. However, when social learning engagement is too strong, there will not be enough new knowledge created in the organization due to less innovation engagement. Gradually the systemic diversity in agents' solutions is fading away while the environmental turbulence is still strong enough to bring in brand new and diverse problems. Under such a fatal situation, the organizational performance inevitably declines. Thus, the non-monotonicity should depend on the turbulence of the environment. The more turbulent the environment, the more innovation efforts are needed for solving new problems. To investigate the influence of environmental turbulence on the non-monotonicity, another set of simulation sessions are carried out under a relatively stable environment. This time, the intensity of environmental turbulence $1-\sigma$ is tuned from 0.25 to 0.05, while the inter-temporal goal variability ρ is tuned from 2 to 1. With such designs, simulations are performed with fixed $\mu_i^{in} = 0.25$, and incrementally increased social network connectivity $\mu_i^{im} = 0.05$, $\mu_i^{im} = 0.3$, $\mu_i^{im} = 0.5$, $\mu_i^{im} = 0.8$. The results shown in Figure 4-15 indicate that the organizational performances under the stable environment continuously strike without any decline. Moreover, the overall organizational performances are higher and the standard deviations are lower (less than 0.22), because sharing existing knowledge among agents is good enough for solving recurrent problems.

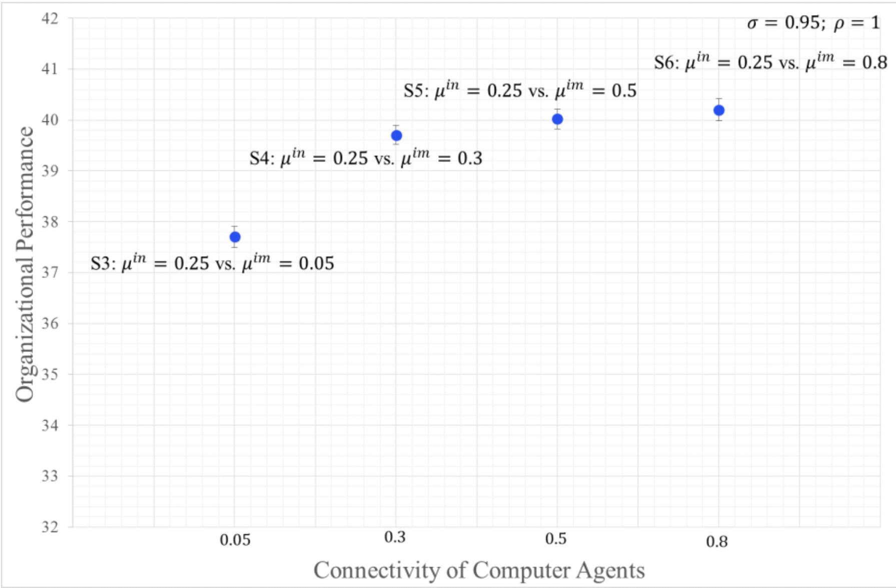

Figure 4-15 Monotonicity in Organizational Performance under Stable Environment

4.6.2 Results on Human Bounded Rationality Influences

To further investigate on human bounded rationality impact on individual decision behavior at microscopic level and organizational performance at macroscopic level. More simulation sessions are executed with various exogenous KM Policy settings (Table 4-4).

Table 4-4 Further Testing Various KM Policies in Simulation

Simulation Sessions	**Innovation (μ_i^{in}) Productivity of New Knowledge**	**Imitation (μ_i^{im}) Connectivity of Social Network**
G1	0.25	0.05
G 2	0.25	0.2
G 3	0.25	0.3
G 4	0.25	0.5
G 5	0.25	0.6
G 6	0.25	0.8
G 7	0.25	0.95

Figure 4-16 reveals that steady-state organizational performance is non-monotonically enhanced along the increase of social network connectivity from G1 to G7 when productivity of new knowledge is low. The steady-state collective decision behaviors on choosing innovation in Figure 4-17, continuously decrease when the connectivity is getting better. The cause of this phenomena is discussed in the later section.

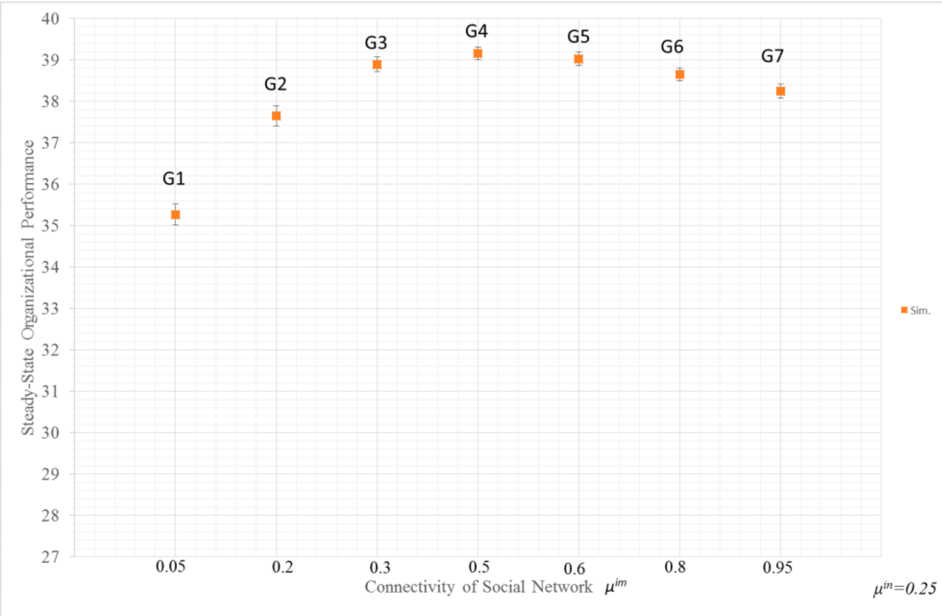

Figure 4-16 Steady-state Performance in Simulation from G1 to G7

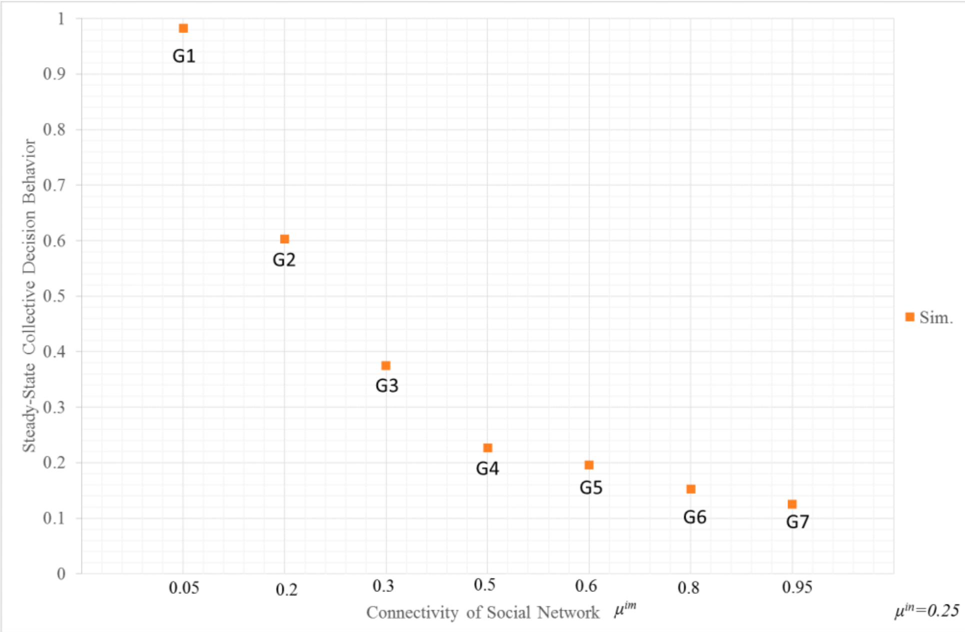

Figure 4-17 Collective Decision Behaviors in Simulation from G1 to G7

To compare with the simulation data, more gaming sessions are played by volunteers. With the resource restriction, only 15 sessions are played with 90 participants. The parameter settings are the same with the simulation which are listed in Table 4-5.

Table 4-5 Further Testing Various KM Policies in Behavioral Experiments

Experiment Sessions	**Innovation (μ_i^{in}) Productivity of New Knowledge**	**Imitation (μ_i^{im}) Connectivity of Social Network**
Game 1 x 4	0.25	0.05
Game 2	0.25	0.2
Game 3 x 2	0.25	0.3
Game 4 x 3	0.25	0.5
Game 5	0.25	0.6
Game 6 x 3	0.25	0.8
Game 7	0.25	0.95

Steady-state collective performance $\bar{\pi}(t)$ of each experiment is depicted in Figure 4-18, for comparison. Because the probability of choosing innovation $\bar{q}(t)$ for human agents is an endogenous factor, the developmental process is impossible to be obtained. Hence, overall $\bar{q}(t)$ of each game is calculated and depicted in Figure 4-19 for further discussion.

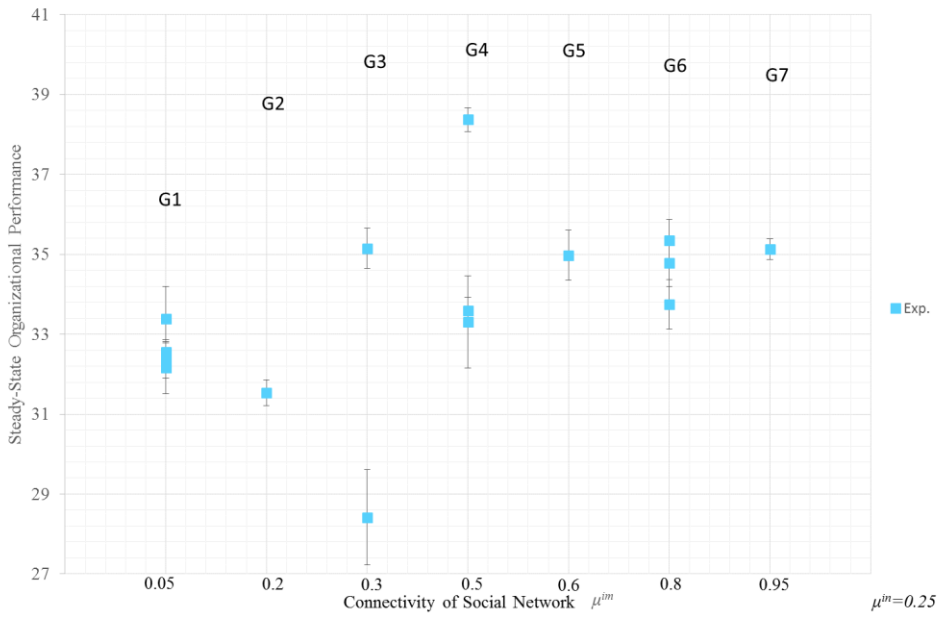

Figure 4-18 Steady-state Performance in Experiments from G1 to G7

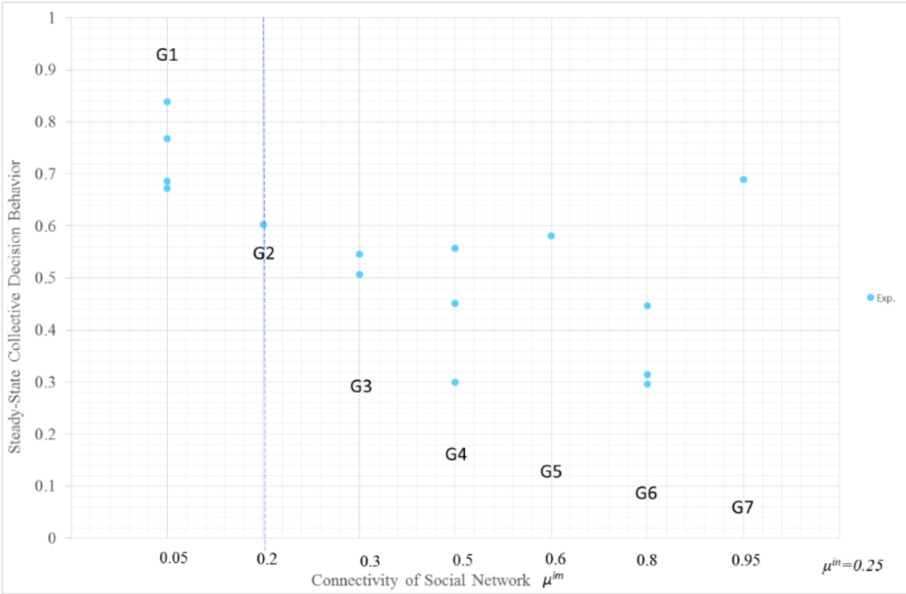

Figure 4-19 Collective Decision Behavior in Experiments from G1 to G7

4.7 Further Comparison of Simulation and Experiments

The crucial investigation is to examine whether the human agents make rational or behavioral decisions. In the simulation implementation, it is assumed that the computer agents update the probability of innovation/imitation based on reinforcement learning (Equation 4 and 5), however, in the experiments human agents adjust this endogenous probability based on their own tacit assumptions. After merging both simulation and experiments decision indicator $\bar{q}_i(t)$ of each game together. As shown in Figure 4-20, although samples of experiments are limited, still G2 can be clearly manifested as a critical point with both simulation and experimental results align with each other, separating two distinct patterns. On the left side of G2, human agents are not as rational expected and are prone to choose imitation while it is extremely more difficult to succeed than innovation given the connectivity of social network is extremely low ($\mu_i^{in} = 0.25\ \ vs. \mu_i^{im} = 0.05$). On the right side of the G2, along with increasing connectivity of the social network human agents are prone to innovation even while it is more difficult to succeed than imitation given that the productivity of innovation is fixed low $\left(\mu_i^{in} = 0.25\ \ vs.\ \ \mu_i^{im} = 0.3\ \text{ to }\ \mu_i^{im} = 0.95\right)$. Apparently, human agents have a tendency in choosing a strategy that is comparatively more difficult to succeed.

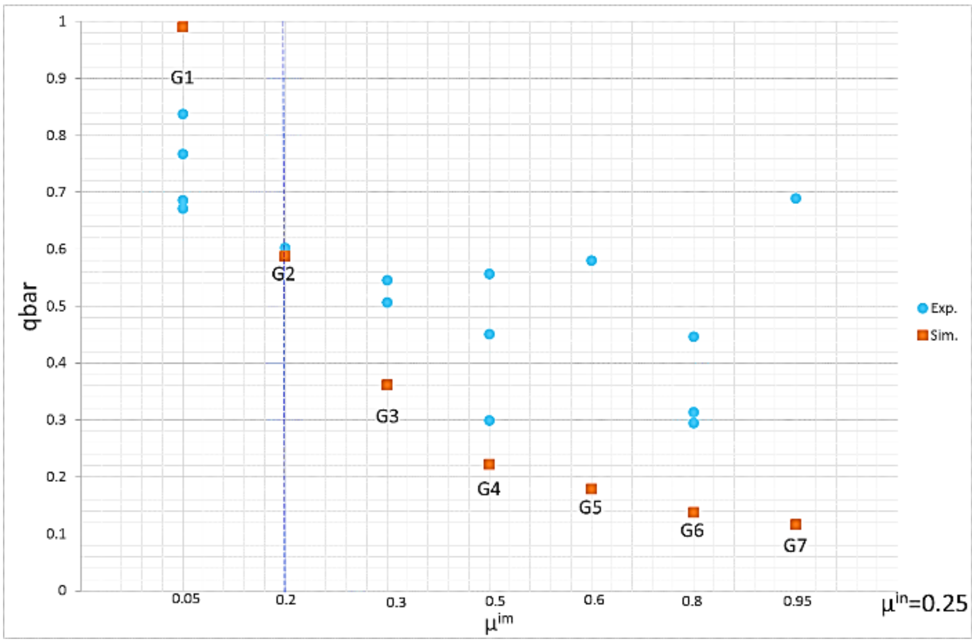

Figure 4-20 Collective Decision Behaviors Comparison

4.7.1 The Scarcity Heuristic

From the empirical data obtained from human experiments, the surprising patterns indicating Scarcity Heuristic in human agents' decision making. As shown from the literature, scarcity heuristic is a mental shortcut that place a value on an item based on how easily it might be achieved or lost, the more difficult it is to achieve, the more value that item has (Lynn, 1989). Gigerenzer (1991) further states that the scarcity heuristic can ease the cognitive load of making a decision but in certain cases it can lead to systemic errors or cognitive bias.

4.7.2 A Proposed Model Modification

In the original design, a version of experience-weighted attraction (EWA) is adopted to update the probabilities as shown in Equation 3 and 4, indicating the higher successful rate of the chosen strategy, the higher the probability of choosing it again in the next round. To modify the attraction of the strategy for probability updating in the scarcity heuristic decision way, a weighting value Δ^{in} or Δ^{im} is induced which value depends on both successful rate S of the chosen strategy and the network connectivity denoted by $\hat{\mu}^{im}$ which is relative to the critical point network connectivity μ^{im}_{crit}, and it is calculated below:

$$\hat{\mu}^{im} = \frac{\mu^{im} - \mu^{im}_{crit}}{\mu^{im}_{crit}} \ . \tag{15}$$

The modification of agents' attractions to a strategy is proposed below:

$$B_i^{in}(t+1) = \begin{cases} \phi B_i^{in}(t) + \Delta^{in}, & \text{if adopted} \\ \phi B_i^{in}(t), & \text{otherwise} \end{cases}. \tag{16}$$

where $\Delta^{in}\ (S, \hat{\mu}^{im}) = S \cdot H(\hat{\mu}^{im}) \cdot f(\hat{\mu}^{im})$, indicating the lower the successful rate of the strategy, the higher weight agents will put once it is successful with a Heaviside function.

$$B_i^{im}(t+1) = \begin{cases} \phi B_i^{im}(t) + \Delta^{im}, & \text{if adopted} \\ \phi B_i^{im}(t), & \text{otherwise} \end{cases}. \tag{17}$$

where $\Delta^{im}\ (S, \hat{\mu}^{im}) = S \cdot (1 - H(\hat{\mu}^{im})) \cdot g(\hat{\mu}^{im})$. Note that f is an increasing and g is a decreasing function of $\hat{\mu}^{im}$, though the detailed form is unknown and maybe depend on individual characteristic.

New simulation results are obtained and depicted in Figure 4-21 after considering scarcity heuristic in the model modification. Qualitatively, the computer agents' decision behavior is closer to human agents' behavior now. However, detailed and accurate causal relationship among weighting value, relative value of μ^{im}, and strategy successful rate needs to be further explored and tested.

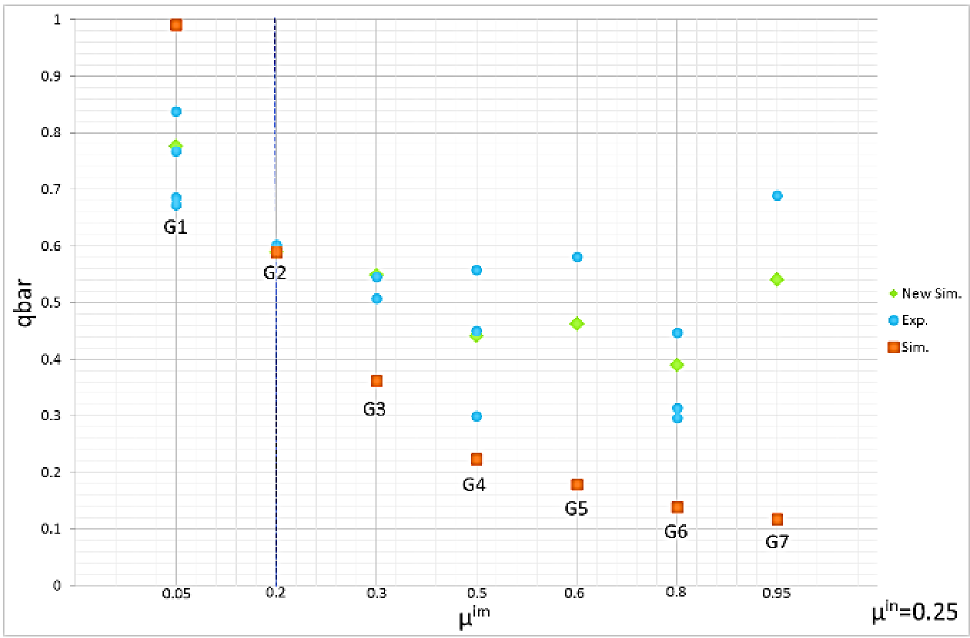

Figure 4-21 New Collective Decision Behaviors Comparison

4.8 Implications

4.8.1 Empirical Evidence from Behavioral Experiments

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 Figure 4-12, only Player 1 on the horizontal axis always learns intra-groupy while others all attempt inter-group learning, even the information, intra-group learning is more helpful, has been given. Even more surprisingly, Player 6 on the horizontal axis learns more inter-groupy than intra-groupy, revealing a strong irrationality. Whether the irrational behaviors are due to the curiosity, social preference or heuristics, so far it cannot be confirmed. Yet, it suggests a need for re-examine the reinforcement learning rule in ABM. Therefore, the gaming experiment provides a crucial support for model improvement in the future.

4.8.2 The Integration of Agent-Based Modeling and Behavioral Experiments

One of the unique characteristics and advantages of multi-agent simulation is the versatility. It can produce emerged macroscopic phenomenon based on the microscopic individual interactions and offer internal structure, process and state scalable view of results for investigation. In this study, the simulation discovers the non-monotonicity on organizational performance alongside the network connectivity improvement which cannot be feasibly achieved using traditional costly qualitative or quantitative methodologies. Moreover, based on such a versatile tool, policy makers can design new strategies and policies for the organization, 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 skillset pre-requisites; sacrifice overhead cost; interrupt daily operations or introduce panic to employees.

The advantages of behavioral experiment are mentioned previously in Chapter 3. Although simulation and experiment can be used as standalone methodology, both have limitations that can be overcome through integration. The simulation can be used as a roadmap for the experiment while the experiment can be used for verification and refinement of the developed ABM with supplementary information from the reality. When integrated, as demonstrated in this study, both can reinforce and elevate each other delivering more insightful and reliable results for evolutionary and behavioral KM study and organizational performance optimization.

CHAPTER 5 THE EXTENDED KM GAME

This chapter explains the extended KM game in details. Followed by some background investigation on incentives for KM, a conceptual framework is established targeting two dilemmas. Then the extended KM is described again in ODD protocol. For the implementation, it is firstly implemented in the behavioral experiments with human participants. The conceptual framework is tested, four cases experimenting different administrative KM policies are conducted, and the empirical data is obtained and analyzed, based on which the agent-based model on extended KM game is preliminarily developed and executed.

5.1 Background

On top of the basic game, an extended KM game introducing an administrative *incentive system*, namely a payoff function to knowledge creation and sharing is developed. An incentive is a notion that motivates an individual to perform an action. The study of incentive policies is central to the study of all economic activities: both on individual decision-making and intra-organization cooperation vs. competition. Ultimately, incentives aim to provide value for money and contribute to organizational success (CIPD House, 2013). Administrative policy-makers always strive to establish KM incentive policy that is both suitable for maximizing organizational performance and fair for motivating the agents. Such policy should have the following features: good efforts pays off; every agent has the equal chance to be the top player; and bottom player has the chance to bounce back. However, many difficulties are confronting administrators, for example, how much reward should be allocated on each KM action? What is the relative reward tradeoff between innovation and imitation? When should adjust this ratio? How to promote good competition while maintaining a minimal level of cooperation? What conditions change the incentive effectiveness? Through the extended KM game with behavioral experiments and agent-based simulation, such complex and unknown mechanism can be elucidated. The extended KM game acts as an application for facilitating policy-makers to gain better understanding of the internal KM effort, introduce administrative policy interventions, and evaluate corresponding effectiveness.

5.2 Conceptual Framework

The extended KM game is concerned with two dilemmas: loss aversion vs. risk seeking as well as competition vs. cooperation. To explain the two dilemma in details and the design of KM incentive systems, the conceptual framework is illustrated in Figure 5-1 and elaboration is as follows.

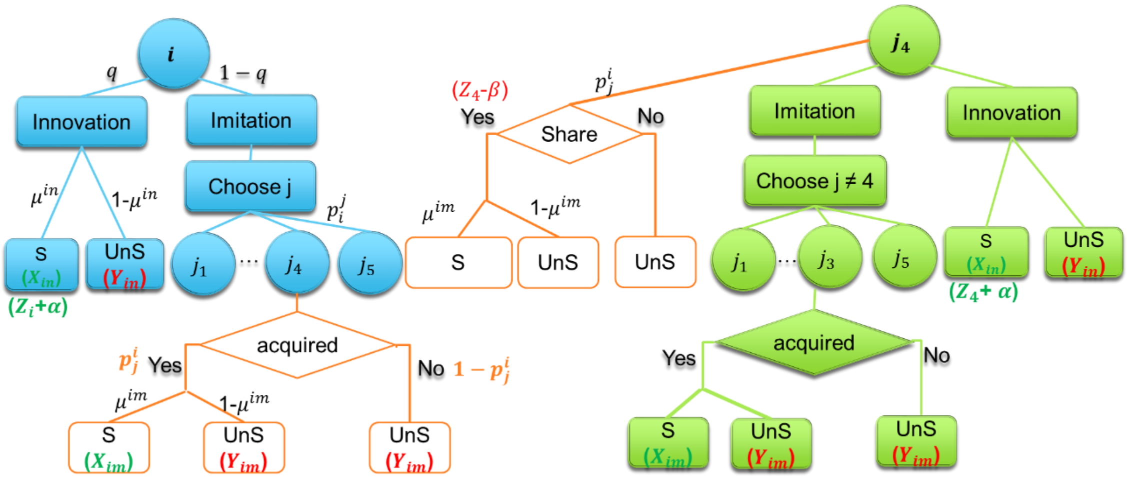

Figure 5-1 Conceptual Framework of The Extended Game

The basic KM game and some important literature, e.g. prospect theory (Kahneman & Tversky, 1979) and advances in prospect theory (Kahneman & Tversky, 1992) imply that policy-making without considering bounded rationality and behavioral decision-making of agents are doomed to fail. These behavioral economics theories reveal that human agents have a hypothetical value function in decision-making that is concave for gains and convex for losses, and much steeper for losses than for gains (Figure 5-2) (Kahneman & Tversky, 1992) and overweight small probabilities and underweights moderate and high probabilities event (Figure 5-3) (Kahneman & Tversky, 1992). Hence, when implementing extended KM game in behavioral experiments, the key task is to find the critical condition for discovering the human attitude towards KM strategies and tracking the evolving choices on KM strategies to obtain the weighting value that human agents place on each strategy.

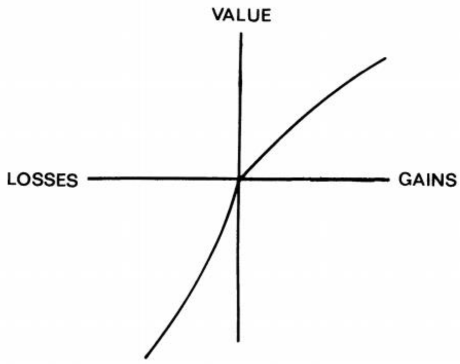

Figure 5-2 A hypothetical value function from Prospect Theory

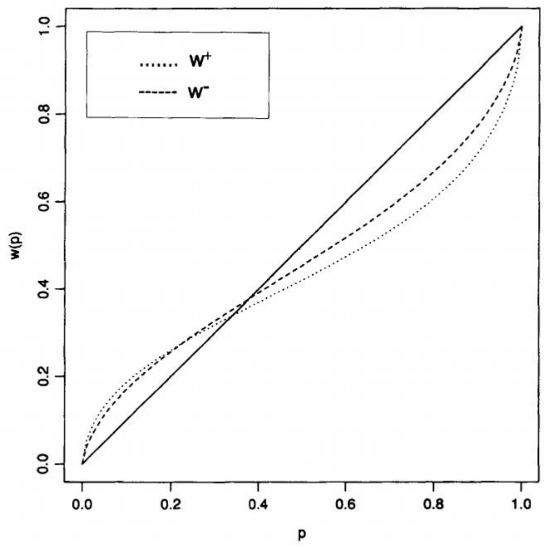

Figure 5-3 Weighting functions for gains and losses from Advances in Prospect Theory

Dilemma One on uncertain payoffs: loss aversion vs. risk seeking

In this dilemma, Innovation has high return (reward: X_{in}) but high risk (cost: Y_{in}) while Imitation has low return (reward: X_{im}) but low risk (cost: Y_{in}). Agents maximize income by a freedom of choice on either innovation or imitation. If agent i chooses to innovate, under probability μ^{in} which is the innovation capability of agents, knowledge creation can be successful, agent i gains high return (reward: X_{in}), meanwhile his/her knowledge uniqueness Z_i will increase significantly ($Z_i + \alpha$); Under the probability $1 - \mu^{in}$, knowledge creation is unsuccessful, hence agent i suffers the high risk (cost: Y_{in}). If the agent i chooses to imitate, he/she needs to choose the imitation target, if the target agrees to share his/her knowledge, agent i's imitation is successful and he/she gains low return (reward: X_{im}), but his/her knowledge uniqueness will not increase through imitation; if the target disagrees to share his/her knowledge, agent i's imitation is unsuccessful and he/she suffers low risk (cost: Y_{in}). Whether the target can cooperate or not, it is difficult to predict, the initial probability is 0.5 meaning that either accept or reject, and this risk can be manageable through interactions. When trust or altruism emerged, the probability can grow very high. The extended KM game makes sure that theoretically, the expected utility for either innovation or imitation is the same. At the end of each time, agent's performance π_i and income I_i will be updated, so he/she can adjust the probability of choosing innovation q or imitation $1 - q$ in the next time. If agents choose more innovation with high q, they display a risk seeking behavior while agents choose more imitation with high $1 - q$, they display a loss aversion behavior.

Dilemma Two on Social Preference: Competition and Cooperation

At intra-organizational level, coopetition occurs between individuals or functional units. Based on game theory and social interdependence theories, some studies investigate the presence of simultaneous cooperation and competition among functional units, the antecedents of coopetition, and its impact on knowledge sharing behaviors (CIPD House, 2013). For example, the notion of cooperative knowledge sharing is developed to explain mechanisms through which coopetition influences the intensity of knowledge sharing among human agents (Kimiz, 2013). The underpinning statement is that while organizational function units need to cooperate, they are likely to face some competition dilemma. It is because being selfish and compete with others is innate human nature which can be considered as a default choice of human agents, except some particular situation, e.g. with relatives who share the same genes. Under what conditions cooperation can arise is the central concern when designing the incentive system.

In recent years, the concept of 'Coopetitive Knowledge Sharing' (Ghobadi, 2011) is also emerged that tackles:

(1) How coopetition should be conceptualized (Ghobadi, 2012a);

(2) What forms coopetition (three formative constructs of outcome (goal, reward), means (task related), boundary (friendship, geographical closeness, sense of belonging)

interdependencies) (Ghobadi, 2012b);

(3) How coopetition and its interrelated determinants interact and influence knowledge sharing behaviors among function units.

Thus, this topic is getting attention for investigation in the KM field. Based on seminal work laid ahead, Dilemma Two aims at utilizing incentive policy to explore the agents KM behaviors when facing a competition vs. cooperation dilemma and how they choose to interact with each other and how their income is affect by others' choices. In this dilemma, the innovation and imitation payoffs and the probabilities for success accordingly are the same with the dilemma one. This dilemma forces agents to decide strategically when cooperation is requested. The only way for agents to improve individual knowledge uniqueness Z_i which is through successful innovation. There is a chance that the knowledge uniqueness Z_i decreases which is through knowledge sharing and cooperating with other agents. If cooperation decreases the knowledge uniqueness, why should agents accept to cooperate? What motivate them to make such hurtful decision? With the knowledge bonus introduced, agents have high motivation to cooperate to gain more knowledge bonus even cooperation makes the knowledge uniqueness decreases. At each round, a collective knowledge bonus can be shared by agents which is determined by the cooperation rate of the round multiplied by bonus unit.

The higher the cooperation rate, the large the bonus budge can be shared. How much individual knowledge bonus can be gained is determined by agent's knowledge uniqueness. The higher the knowledge uniqueness, the bigger proportion of the collective knowledge bonus can be gained. Hence, individual agent's knowledge uniqueness level relative to the organizational average, and organizational cooperation culture are both crucial for gaining higher knowledge bonus.

The decision framework in Dilemma Two is specified as follows: when an agent chooses innovation, he/she faces high return (reward: X_{in}) high risks (cost: Y_{in}), and an increase in ranking position relative to the organizational average ($Z_i + \alpha$). This ranking information is one of the determinants for knowledge bonus yielded at each round on top of monetary innovation or imitation reward. When an agent chooses imitation, he/she has low return (reward: X_{im}) and uncertain risk (cost: Y_{im}) because the other agent that he/she chooses to imitate from has a freedom of choice on whether to cooperate or not. The initial probability of cooperate is 0.5. If he/she chooses to share, he/she will have to bear a cost – lower the knowledge uniqueness ($Z_j - \beta$), where $\alpha > 1 \gg \beta$. At the end of each round, agent's performance π_i, income I_i as well as the ranking information Z_i will be updated, so he/she can adjust the probability of choosing innovation q or imitation $1 - q$ as well as social preference matrix p_i^j and p_j^i in the next time.

Agent's income I_i is calculated by independent innovation effort, interdependent imitation, and knowledge bonus which is determined by both individual knowledge uniqueness, and collective social cooperation as shown in the following equation:

$$I_i = q \cdot \left[\mu^{in} \cdot X_{in} - \left(1 - \mu^{in}\right) \cdot Y_{in}\right] + \quad (18)$$

$$(1 - q) \cdot \left[p_j^i \cdot \mu^{im} \cdot X_{im} - p_j^i \cdot \left(1 - \mu^{im}\right) \cdot Y_{im} - \left(1 - p_j^i\right) \cdot Y_{im}\right] +$$

$$f(B) \cdot g(Z_i)$$

Note that $f(B) = \frac{C_{accept}(t)}{C_{request}(t)} \cdot B$ is the bonus budget at time t where $\frac{C_{accept}(t)}{C_{request}(t)}$ is the number of players that accepted the cooperation seeking proportion to number of players that requested the cooperation when Imitation is chosen; $g(Z_i) = \frac{(Z_i - Z_{min})}{\sum_i (Z_i - Z_{min})}$, is agent i's ranking position in the organization according to the comparison between his/her knowledge unique with others, where $Z_i(0) \in [0,1,2]$; μ^{in} is the productivity of a new knowledge is a fixed parameter for each game, e.g. $\mu^{in} = 0.25$; μ^{im} is the helpfulness of the shared knowledge depends on the knowledge uniqueness between agent i and agent j using Heaviside Function

$$H(Z_j - Z_i) \geq 0 \quad \mu^{im} = 1 \;; \quad (19)$$

$$H(Z_j - Z_i) \; < 0 \quad \mu^{im} = 0$$

Knowledge Uniqueness Z_i Update is guided as follows:

If Innovation is successful, knowledge uniqueness increases by:

$$Z_i' = Z_i + \alpha \cdot (Z_{max} - Z_i) \tag{20}$$

If Cooperation is accepted, knowledge uniqueness decreases by:

$$Z_i' = Z_i - \beta \cdot (Z_{min} - Z_i) \tag{21}$$

$$\text{where } \alpha > 1 \gg \beta$$

Under such exogenous reward policy, agents need to act strategically when facing a dilemma between the keeping of individual profit and the optimization of collective performance. Hence, the evolving processes of individual behavioral decision making against collective performance optimization is visualized. Furthermore, the most suitable incentive policy which motivates the individuals and unleash their potential can be identified and tested; and the conditions for cooperative and competing behaviors can be identified. All the notations and parameters are listed below (Table 5-1)

Table 5-1 Parameter Settings in the Extended KM Game

Notation	Definition	Initial Value and Range
μ^{in}	Productivity of The New Knowledge	0.25
μ^{im}	Helpfulness of The Shared Knowledge	0.5
X_{in}	Reward for Successful Innovation	30
X_{im}	Reward for Successful Imitation	6
Y_{in}	Cost for Unsuccessful Innovation	10
Y_{im}	Cost for Unsuccessful Imitation	2
$Z_i(0)$	i's Initial Knowledge Uniqueness	0 or 1 or 2
B	Bonus Unit	20
π_i	i's Performance: No. of Problem Solved	0
N	Number of players	6
p_i^j	Probability of i chooses j	1/N
p_j^i	Probability of j cooperates with i	0.5

To observe agents' evolving choices, learning and adaptation, social interaction at microscopic level and to explore the organizational outcomes at macroscopic level. The following measurements will be calculated.

The microscopic evaluation includes:

- Individual Decision Behavior q
- Individual Performance π_i
- Individual Knowledge Uniqueness Z_i
- Individual Income I_i
- Income breakdown: income from innovation, imitation and knowledge bonus

The macroscopic evaluation includes:

- Collective Decision Behavior $\bar{q}$
- Collective Performance π
- Collective Cooperation Rate Coop%
- Organizational Knowledge Uniqueness $\bar{Z}$
- Organizational Resource delegating to Incentive System $\sum_i I$ and its breakdown

5.3 ODD Protocol

The extended KM game is described in the format of ODD Protocol as follows:

Overview – Purpose

To design the agent's decision-making conceptual framework based on two dilemmatic scenarios with a payoff function; To implement the extended KM game in behavioral experiment, gain empirical evidence and observation, and validate and improve the conceptual framework; To implement the extended KM game in agent-based simulation, utilize the empirical data as input for parameters setting, and generate macroscopic and long-term outcomes for analysis; To identify potential emerged properties e.g. culture and norms that may be critical to the administrative policy-making. The specific aim for establishing the extended game is to explore how to effectively promote innovation while maintaining a cooperative culture

Overview – Entities, State Variables, and Scale

There are two entities in the extended game, namely agents and the organization. Agents are characterized by individual performance (number of problems solved), income (rewards and bonus earned), and knowledge uniqueness. The organization is characterized by collective performance (total number of problems solved), organizational decision-making behavior, organizational knowledge uniqueness, organizational structure, organizational cooperation rate, organizational resources used for KM. To better probe into the relationship between organizational incentive policy and agents' behavior, the content of the tasks is simplified, since it is insignificant to the research purpose. In other words, N agents in the organization ($i \in \{1, 2, \ldots, N\}$), they only need to know under certain probability, innovation or imitation will be successful/unsuccessful regardless what kind of tasks they are solving.

Overview – Process Overview and Scheduling

At each period t, each agent needs to choose either to innovate (knowledge creation) or imitation (acquiring shared knowledge), at the same time, if the agent is chosen for knowledge sharing request, he/she needs to choose whether to cooperate or not. If the new knowledge helps the agent improve individual performance and gaining reward, the probability of choosing the same knowledge strategy and the same knowledge worker (if imitation is chosen) will be updated and the individual income together with knowledge uniqueness will be updated as well, following that the organizational decision behavior, structure concentration, and collective performance measure will be updated.

Design Concepts – Emergence

With knowledge bonus introduced to the system, the organizational cooperation and structure is emerged.

Design Concepts – Adaptation

In order to strategically gain more income, agents are actively adapting and adjusting the decision-making on KM strategies and social cooperation.

Design Concepts – Objectives

The objective of agents is to maximize income gains through KM effort.

Design Concepts – Learning

Agents are learning from past experience and also from social observations on how others behave and how the collective system behaves.

Design Concepts – Prediction

Agents can predict how likely each KM strategy will bring back what outcomes and how likely other agents will cooperate with them. They can also roughly predict the organizational cooperation rate as well as their positions in the social system and hence how much they can gain from knowledge bonus.

Design Concepts – Sensing

Agents can sense who they can learn from and their own relative positions in the system.

Design Concepts – Interaction

There is direct interaction and indirect interaction in the extended game. Direct interaction is when imitation is chosen. Agents have the freewill to choose who they want to seek for help. They can also decide whether to cooperate or not when someone is seeking for help. Indirect interaction is when knowledge bonus is allocated to each agents. The collective cooperation rate decides how much bonus can be gained in one period. Hence, the individual bonus gaining depends on both self-effort and others' choices. This direct interaction and indirect interaction is a key feature in the extended game since it creates a social dilemma bridging the organizational and individual interests together.

Design Concepts – Stochasticity

The successfulness of innovation is determined by an adjustable probability.

Design Concepts – Collectiveness

In the organization, there are N agents. Unlike the basic game, agents in the extended game are equal individuals without group identities. To better serve the purpose in the extended game, group is no longer essential, hence can be eliminated for simplification.

Design Concepts – Observation

Every agent's decision choices and interactions are recorded in the database. Knowledge uniqueness, income gaining, number of problem solved, organizational knowledge uniqueness, cooperation rate and etc. are calculated period by period at the real time.

Details – Initialization

At the beginning of each game, agents' initial attraction and probability of choosing each KM strategy and each other for social learning are initialized.

Details – Input Data

There is no additional input data or external sources used.

Details – Submodels

There are two submodels in the extended KM game. One is on choosing KM strategies, in other words, the high risk high return one – innovation or the low risk low return one – imitation. The other is on choosing whether to cooperate or compete, since for cooperation, the chosen agent has to suffer a cost of lowering his/her knowledge uniqueness when sharing the knowledge with other agent, whereas for competition, one may gain less bonus since the cooperation rate decides the bonus at each time. The higher the cooperation rate the more bonus they can share among each other collectively.

5.4 Implementation in the Behavioral Experiments

The behavioral experiments for the extended KM game take place in Department of Physics, Fudan University, Shanghai, China. There are several reasons for conducting the experiments in China using Chinese language instead of in Japan using English. First of all, it is easier to recruit many student participants in a short time, so the scheduling pressure can be largely reduced; second, the incentive budget for motivating and rewarding the participants can be less expensive than conducting in Japan; third, it is better to use native language to conduct the game so understanding ambiguity and unnecessary noise can be minimized.

The purpose for implementing the extended game in the behavioral experiments first is to test the proposed conceptual framework, gain empirical observations, and demonstrate the applicability of the extended KM game for exploring various administrative interventions.

After considering the time and resource availability, four games exploring different administrative KM incentive policies are decided. Game One is the baseline version used as a controlled group for comparison; Game Two is designed with a big knowledge bonus at each round. Bonus unit is tuned from $B = 20$ to $B = 30$ aiming at promoting organizational knowledge uniqueness; Game Three is with reputation information disclosing each agent's past history of cooperation seeking and giving aiming at promoting cooperative culture; and Game Four is with diversified agents meaning that each agent has different innovation capabilities, e.g. $\mu_1^{in} = 0.1; \mu_2^{in} = 0.2; \mu_3^{in} = 0.1; \mu_4^{in} = 0.4; \mu_5^{in} = 0.1; \mu_6^{in} = 0.6$, aiming at promoting diversity and organizational performance for optimization. Game Two requires financial delegation from the organization; Game Three uses information control and social incentives; Game Four utilizes human resource hiring strategy to create a diversified mix of employees. The effectiveness of each intervention, agents' adaptive interactions, and collective outcomes will be revealed and compared.

Like the basic KM game, the implementation process includes game preparation and gaming software development; participant recruitment, scheduling, briefing, and warm-up trials; four gaming sessions execution; and data analysis. In game reparation and gaming software development, the conceptual framework on two dilemmas is finalized.

After settling the aim of the experiments, all the desired features, functions, and user interface can be further designed and communicated with the software engineer. The gaming software is developed in accordance with the conceptual framework illustrated in the conceptual framework. It is written in Python and has four modules, namely player interface, control panel, computation engine, and database. The screenshots of user interface are captured in Figure 5-4.

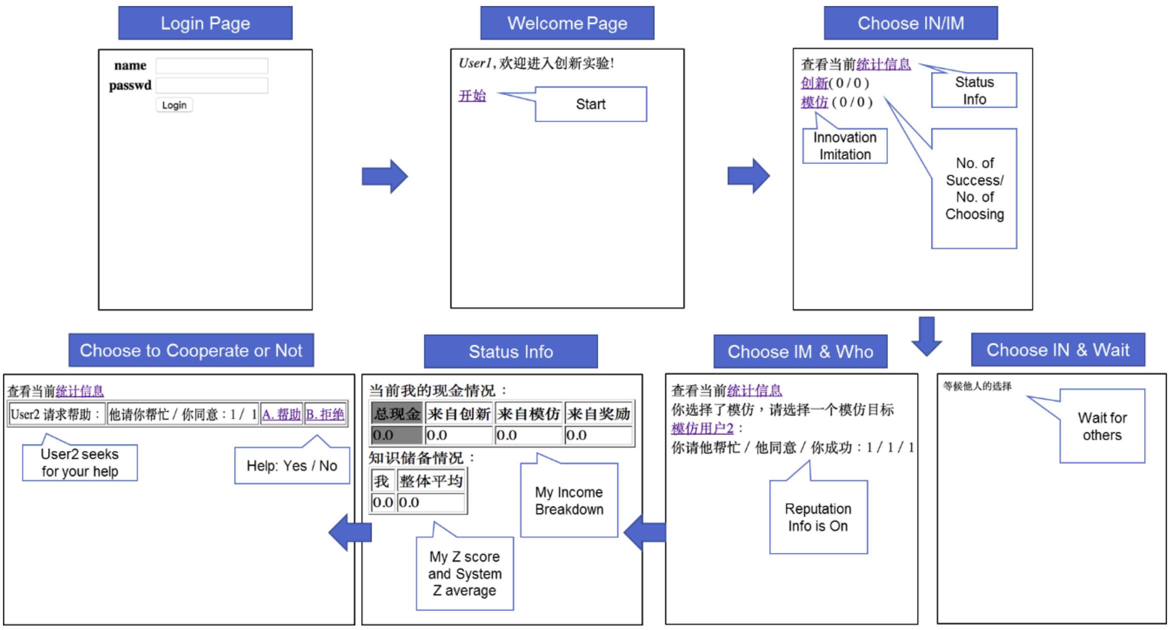

Figure 5-4 Screenshots of Player Interface

There are 12 graduate students recruited to participate in the game. There are another 2 research assistants facilitating the experiments since they are experienced in conducting behavioral experiments. Six participants are needed for each game. Hence, participants are divided into two groups playing two games at the same time in separate rooms. Each participant played two sessions. They are randomly assigned with different User IDs and passwords, so no prior preference on choosing friends or bias is introduced to the experiment. Before formally play the games, all the participants attend the briefing session as well as the warm-up trial plays, hence, they are clear about the rules and familiar with all the functions and features. For example, when user1 logs in, he/she can press start and choose to innovate or imitate bearing in mind that the expected payoffs are equal. If he/she chooses to innovate, they do not need to choose people and wait for others finish choosing. If he/she chooses to imitate, then they need to choose other agent for cooperation seeking. When everyone finish choosing KM strategies, the system will show if there is any cooperation request from other players. Based on “Status Info” including income gaining and knowledge uniqueness Z, one can choose strategically whether to help or reject. At the end of each round (Figure 5-5), a performance, income, and knowledge uniqueness changes summary will be displayed for players to adapt and learn for next action. A screenshot of the control panel is shown in Figure 5-6, hence the facilitator can monitor the game and remind players if they forget to choose or delay the progress. For Game two and four, the bonus unit and innovation successful rate for each agent can be changed in the Python code parameter table. For Game three, the control of additional information on or off can also be adjusted in the Python code. Once the parameters are set, they will not be changed during the game. Each game is played with

50 rounds. Roughly it lasts for 40 minutes each. At the end of the game, participants are rewarded with cash based on their final income gaining. The player with lowest income cannot receive any financial reward as a penalty, however, he/she receive a small souvenir for devoting time. The budget for each game is RMB600. If shared averagely by 5 players, each can gain RMB120 for 40-mins play, which is roughly two to three times higher than the hourly rate for a part-time job. Therefore, it is regarded as a high monetary reward for students. During the game play, participants are highly motivated and engaged.

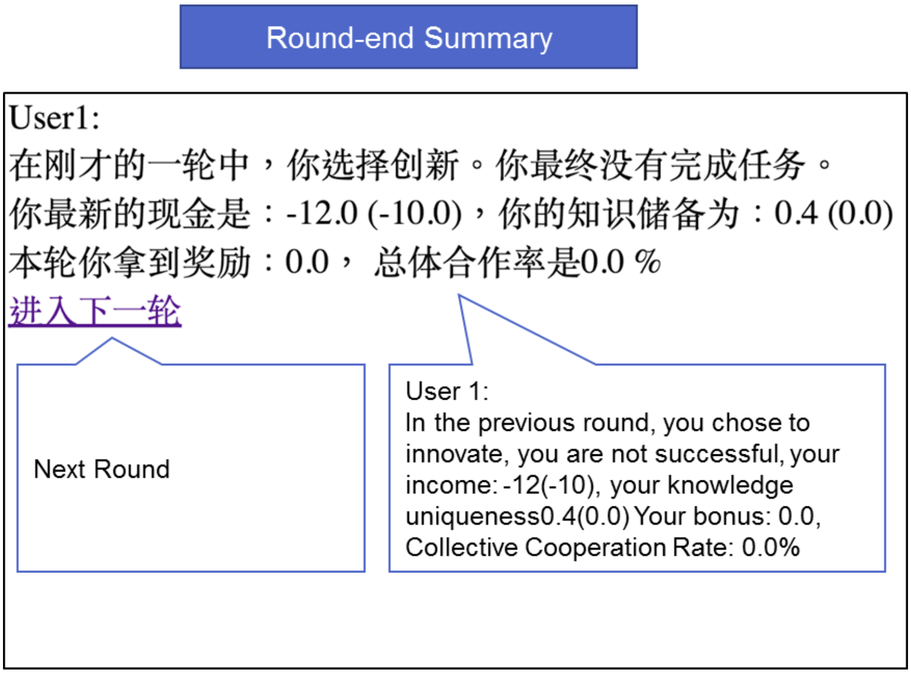

Figure 5-5 Screenshot of Individual Round-end Performance Summary

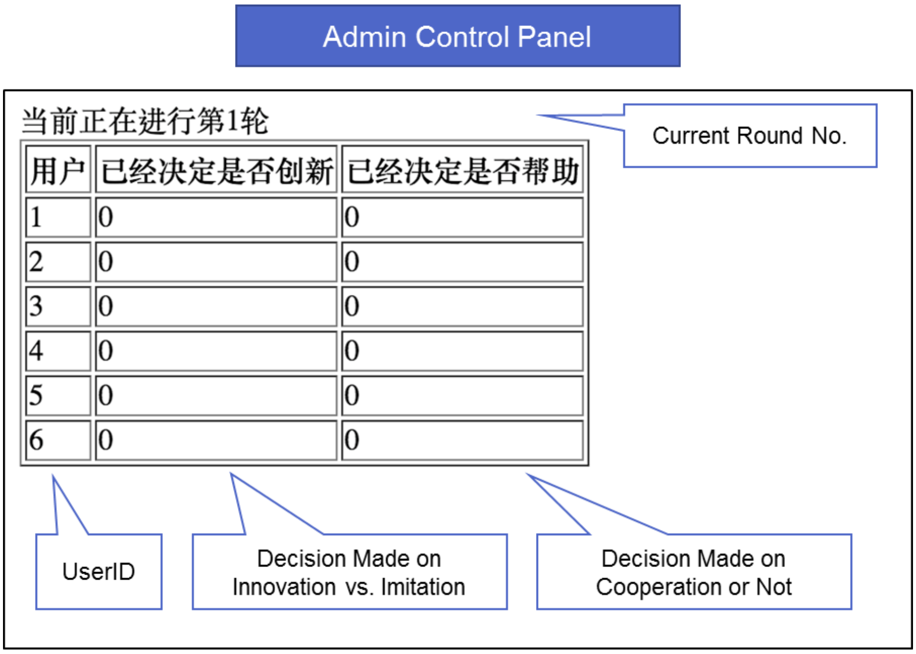

Figure 5-6 Screenshot of Control Panel

Selected snapshot of participants in the behavioral experiments implementation is shown in Figure 5-7.

Figure 5-7 Snapshot of behavioral experiments for The Extended KM Game

5.5 Results Discussion of Behavioral Experiments

Appendix II summarizes all the results obtained from the behavioral experiments and On the left hand side, there is agent's data at microscopic level whereas on the right hand side, it is the organizational outcomes at macroscopic level. To better compare and evaluate the interventions with baseline. Table 5-2 summarizes macroscopic results.

Table 5-2 Macroscopic Results

	Organizational Performance (Problem Solving%)	Organizational Innovativeness $\bar{q}$	Cooperation Culture Coop%	Organizational Knowledge Uniqueness	Bonus Cost
Baseline	22.67%	0.48	36%	0.32	348.66
Big Bonus	29.33%	0.52	69.13%	4.16	975.50
Reputation	40.67%	0.46	94.53%	-0.28	928.66
HR Diversification	59.67%	0.64	94%	4.14	925.00

On Organizational Performance

First of all, comparing with Game One: Baseline, all other cases with administrative interventions are effective since the problem solving rate has been improved, meaning that the organization successfully solve more problems than the baseline setting.

On Cooperative Culture

Also, the organizational cooperation rate (Coop%) has been improved as well, indicating that the interventions are effective on enhancing a cooperative culture of the organization. This is particularly noteworthy in the reputation case and the HR diversity case. When reputation information is disclosed, agents have a strong motivation or social pressure to cooperate with others in order to build a good social image. This finding suggests that reputation or social image is a very effective non-monetary incentive to allow cooperation to arise. In the HR diversity case, when some agents are very good at innovation and having a very high knowledge uniqueness, he/she has the high motivation to capitalize the knowledge, cooperate with others, and transfer the knowledge uniqueness to bonus, while at the same time, some agents are very poor at innovation and having a low knowledge uniqueness, he/she has the high motivation to find the innovative agents for imitation. When knowledge customer finds knowledge supplier, the cooperation rate increases significantly.

On Organizational Knowledge Uniqueness

Not all the three interventions improve organizational knowledge uniqueness ($\bar{Z}$), for big bonus and HR diversity cases, the organizational knowledge uniqueness can be very well maintained, while in the reputation case, the organizational knowledge uniqueness is fading away meaning that the collective knowledge is blended among agents with a strong cooperative culture and knowledge sharing engagement. This makes sense because when reputation information is exposed, agents are more likely to cooperate and share out unique knowledge to build a good reputation even suffering from individual knowledge uniqueness (Z_i) decrease.

On Organizational Innovation Engagement

The reputation case shows that it is not an effective intervention for maintaining good innovation, since it motivates people to choose more imitation indicated by collective decision-making behavior ($\bar{q}$ < 0.5); whereas big bonus and HR diversity cases promote cooperation culture without hurting good innovation.

On Incentive System Effectiveness

Indeed, Game Four: HR Diversity also serves as an evaluation of the developed incentive system. Under good exogenous policy, if one can unleash his/her potential, that indicates the very policy works. For example, the administrator controls the innovation capability of agents μ^{in}, which can be seen as the difficulty of tasks in reality, meaning that the probability of success if innovation is chosen. If the endogenous probability of choosing innovation q_i is better than μ^{in}, that is to say, the agent fully unleashes his/her innovation potential. After further investigating on microscopic agents' decision on innovation q_i as shown in Table 5-3 with individual μ^{in} specified in bracket, only agent 2 did not choose innovation as much as he/she could do, others all demonstrated innovation capability, hence, the incentive system can be regarded as effective.

Table 5-3 HR Diversity Case Microscopic Results

	q	Zi	Iin+Iim	Bonus	Income
User 1	0.52 (0.25)	5.07	60	164.45	224.45
User 2	0.06 (0.25)	0.00	236	0.00	236.00
User 3	0.56 (0.5)	5.28	244	198.22	442.22
User 4	1(0.5)	4.65	460	172.01	632.01
User 5	0.75 (0.75)	4.93	844	159.89	1003.89
User 6	0.98 (0.75)	4.89	708	230.44	938.44

However, there is a design deficiency in Game Four that need to be admitted. When assigning different agent innovation capacity μ^{in}, for stringent comparison with other cases, the average $\overline{\mu^{in}}$ should be the same with other cases ($\overline{\mu^{in}} = 0.25$). Such deficiency may cause bias or errors to the findings, hence, it needs to be eliminated by redesigning the parameters and by repetition of the game in future work to gain statistically significant data.

In summary, the developed incentive system is preliminarily to be proven effective, yet future work still needs to continue. Overall, the most cost-effective administrative intervention for enhancing and balancing all aspects of the organizational outcome is the HR diversity policy. The finding suggests that it is beneficial for organization if administrator hires employees with diversified innovation capability. It also suggests that diversity is crucially important for the complex adaptive system.

5.6 Implementation in the Agent-Based Simulation

Following the behavioral experiments, the baseline game has been preliminarily modeled and implemented in the agent-based simulation. All the functions and features follow the conceptual framework illustrated in extended KM game. However, three variables indicating agent's adaptive decision-making, namely probability of choosing KM strategy q_i, probability of choosing imitation target p_i^j and probability of cooperation r, since they are more complicated and difficult to be determined than the ones in the basic KM game.

For the adaptive learning on choosing KM strategy and adjustment of probability q_i, agents still follows experience-weighted attraction (EWA) learning, updating the strategy attraction factors at each round. However, the extended game has an incentive system that use monetary income to motivate agents for strategic choosing the better options. Hence, a condition is added to the learning rule, that is: if the current round income is less than the recent 5 rounds' average, the strategy attraction factor B_i^{in} for innovation and B_i^{im} for imitation will not be updated. 5 rounds can be adjustable, indicating agents' memory. In other words, only recent 5 rounds' income information can be influential to agents' adaptive learning for next round. For probability of choosing imitation target p_i^j, there is no need to add conditions. Based on previous attraction to each target factor A_i^j makes much sense, meaning that if agent j helped agent i successfully improve the performance, agent j's attraction to agent i in the next round will increase by one unit. For the probability of choosing to cooperation r, based on behavioral experiment empirical evidence shown in Figure 5-8, agents mostly choose to cooperate when their own knowledge uniqueness Z_i is higher than the organizational average Z_{avg}, while choose to reject when their own knowledge uniqueness Z_i is lower than the organizational average Z_{avg}. Hence, the probability of choosing to cooperation r, is a rule-based adjustment.

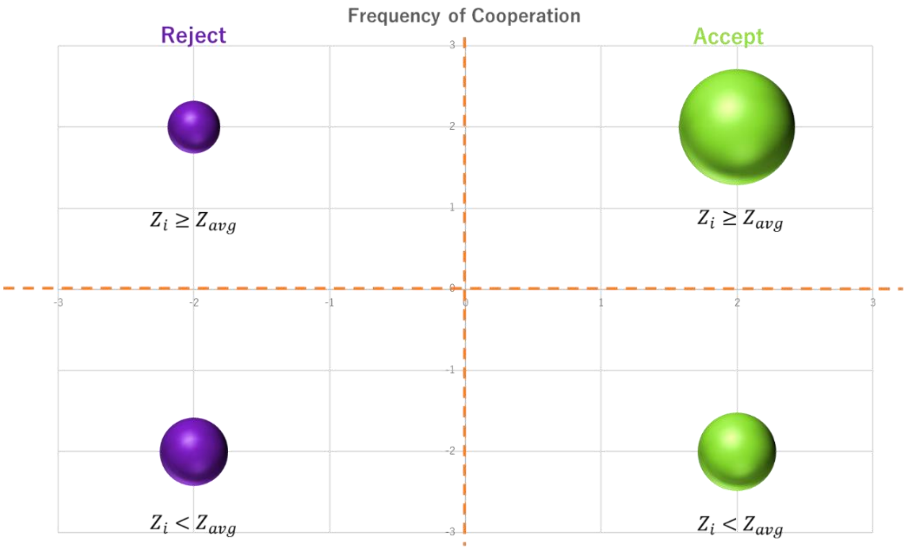

Figure 5-8 Frequency of Cooperation with Reference on Knowledge Uniqueness

5.7 Results of the Agent-Based Simulation

Preliminary results are generated from the Agent-Based Simulation. Each game is run with 1000 rounds. Results are averaged over 10 runs to avoid randomness. Figure 5-9, Figure 5-10, and Figure 5-11 are the baseline case results. Organizational Knowledge Uniqueness, Individual Knowledge Uniqueness, and Individual Income are steadily improved while agents choosing innovation and imitation. Shown in Figure 5-12 , in the organization, after roughly about 200 rounds, specialization has been identified, meaning that some agents are specialized in innovation while others are specialized in imitation. More in-depth and detailed investigations on Agent-Based Simulation results are needed in the future work.

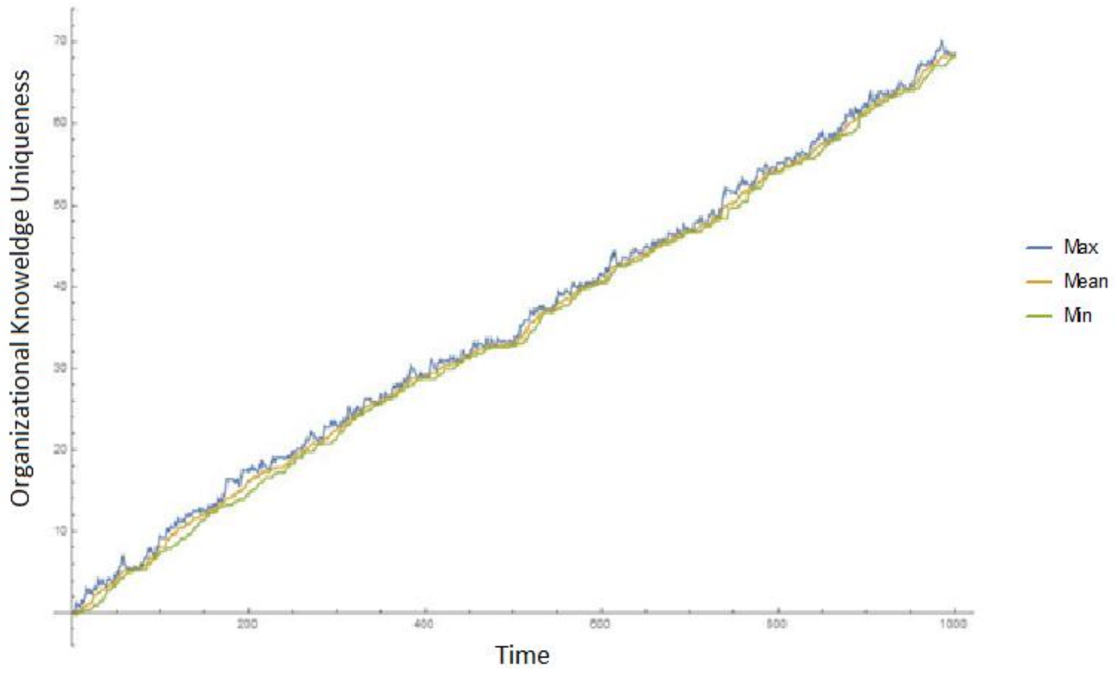

Figure 5-9 Organizational Knowledge Uniqueness in Baseline Case

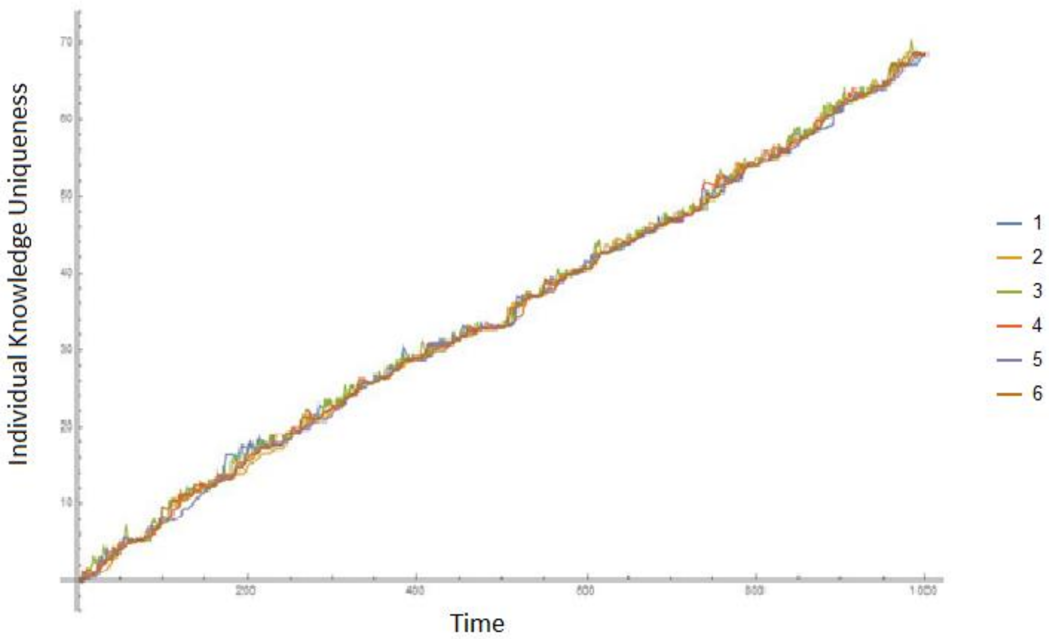

Figure 5-10 Individual Knowledge Uniqueness in Baseline Case

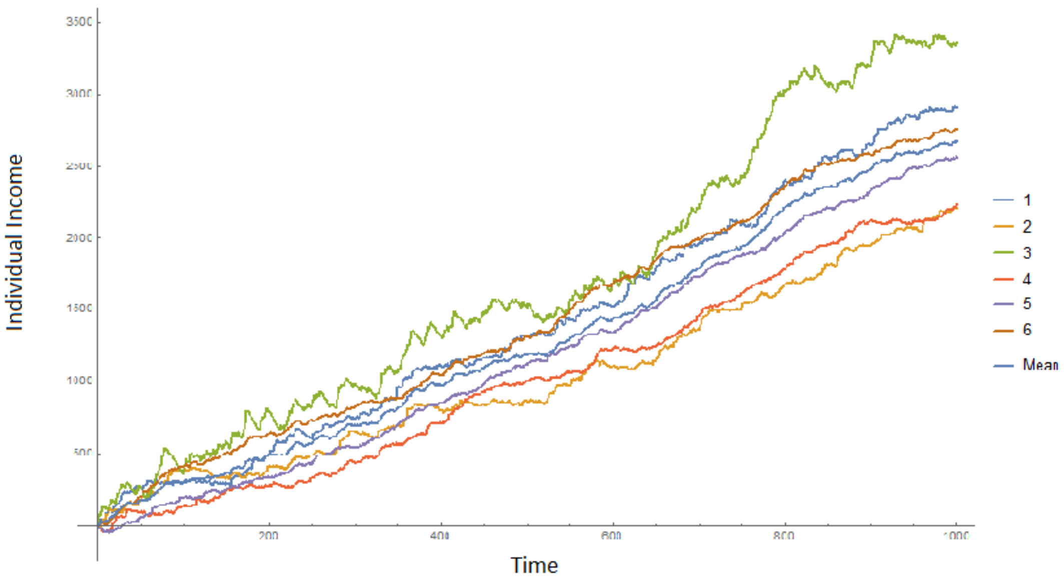

Figure 5-11 Individual Income in Baseline Case

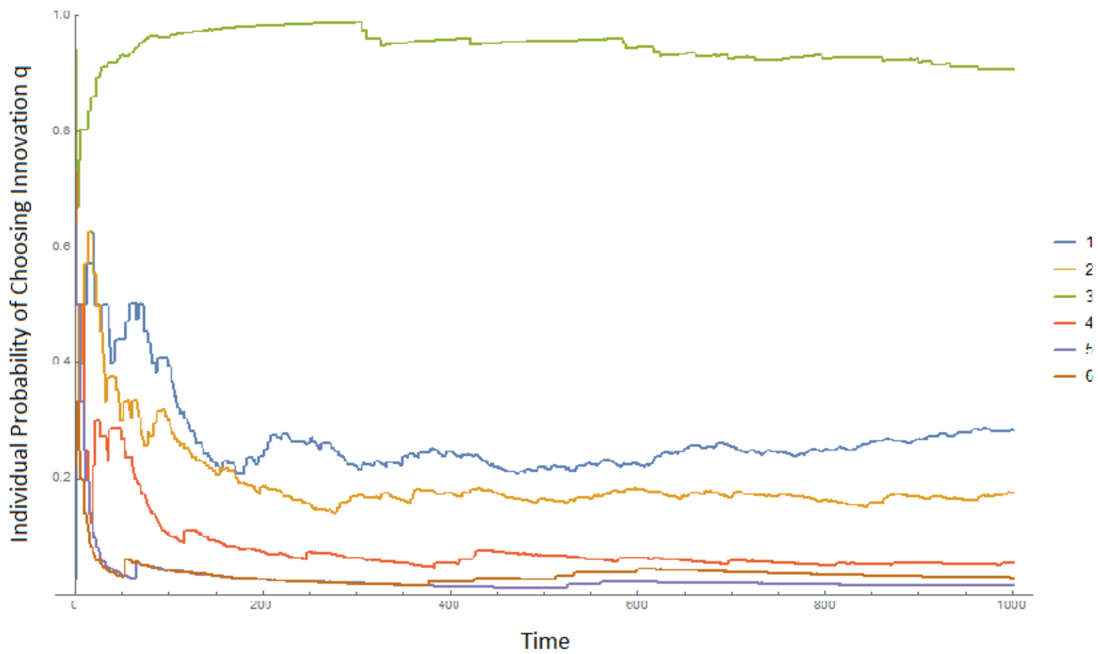

Figure 5-12 Individual Probability of Choosing Innovation in Baseline Case

The results of Game Two with Big Bonus (from $B = 20$ to $B = 30$) and Game Four with HR Diversity ($\mu_1^{in} = 0.1; \mu_2^{in} = 0.6; \mu_3^{in} = 0.1; \mu_4^{in} = 0.4; \mu_5^{in} = 0.1; \mu_6^{in} = 0.2$) are also presented below. However, Game Three with Reputation, is extremely difficult to model at the moment. Hence, it is expected to be achieved in the future study. From the simulation charts obtained from three cases (listed below from Figure 5-13 to Figure 5-20), we can identify the similar findings, for instance, the knowledge uniqueness and income value in HR diversity case are the highest. However, further investigation is needed, and the model verification needs to be done as well.

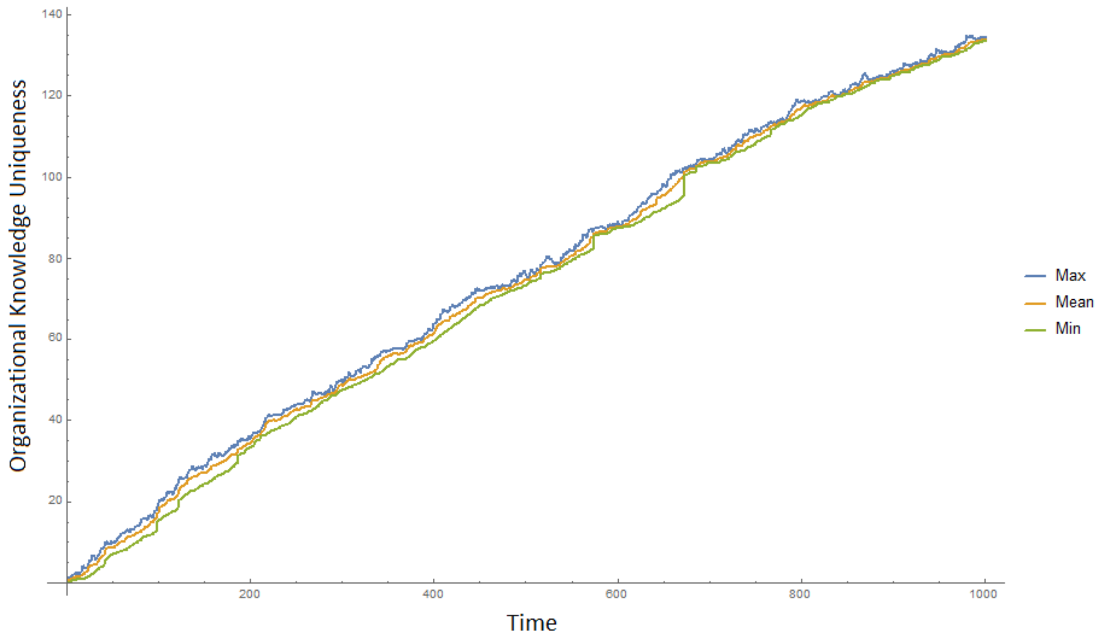

Figure 5-13 Organizational Knowledge Uniqueness in Big Bonus Case

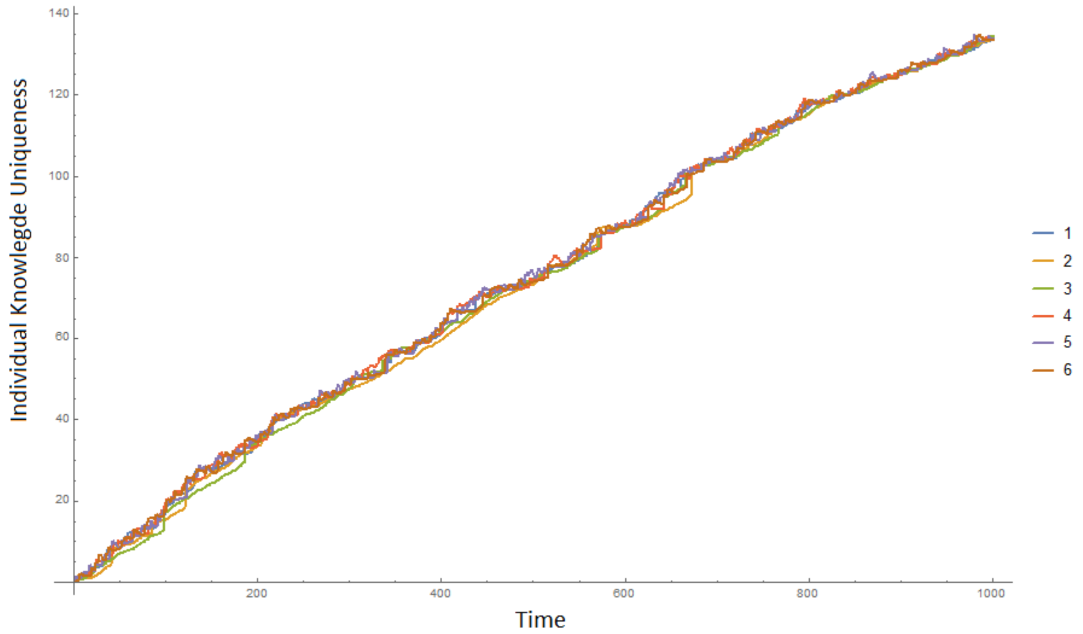

Figure 5-14 Individual Knowledge Uniqueness in Big Bonus Case

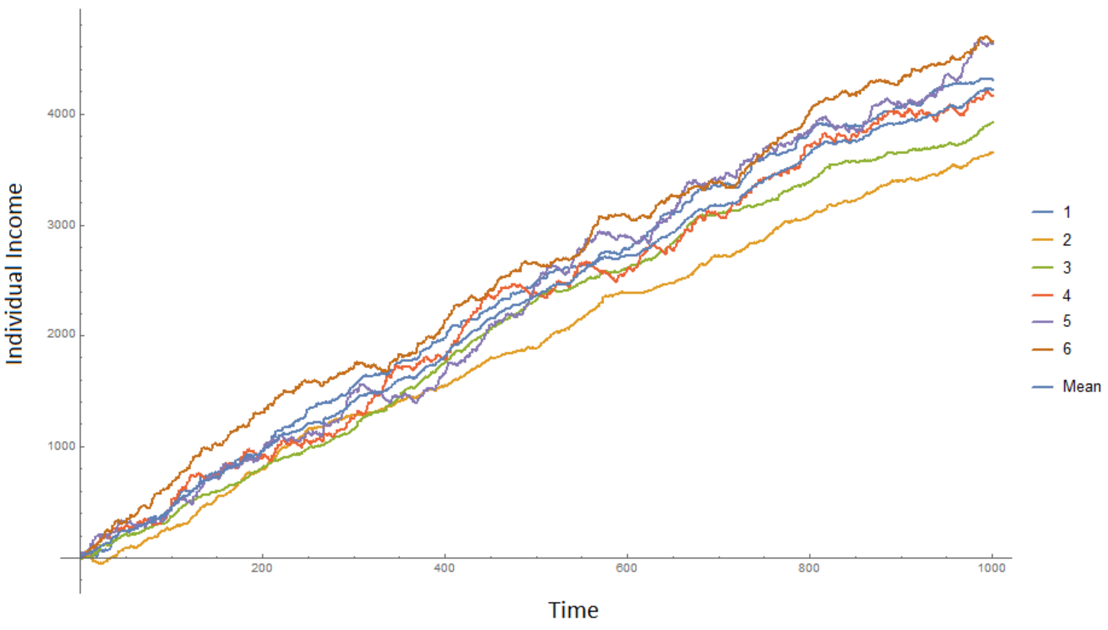

Figure 5-15 Individual Income in Big Bonus Case

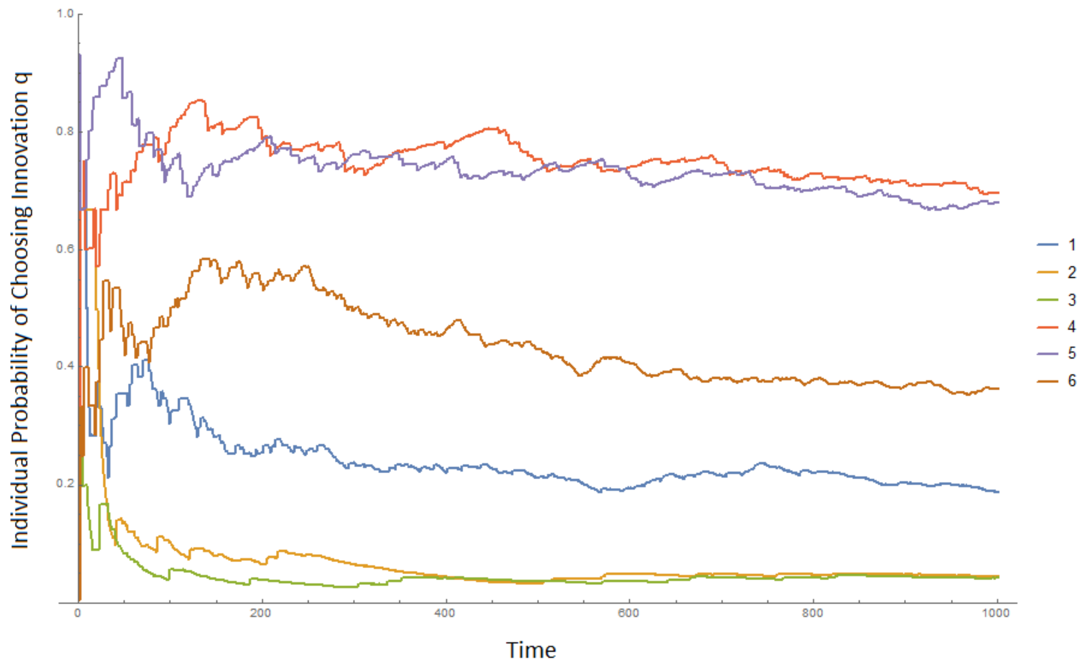

Figure 5-16 Individual Probability of Choosing Innovation in Big Bonus Case

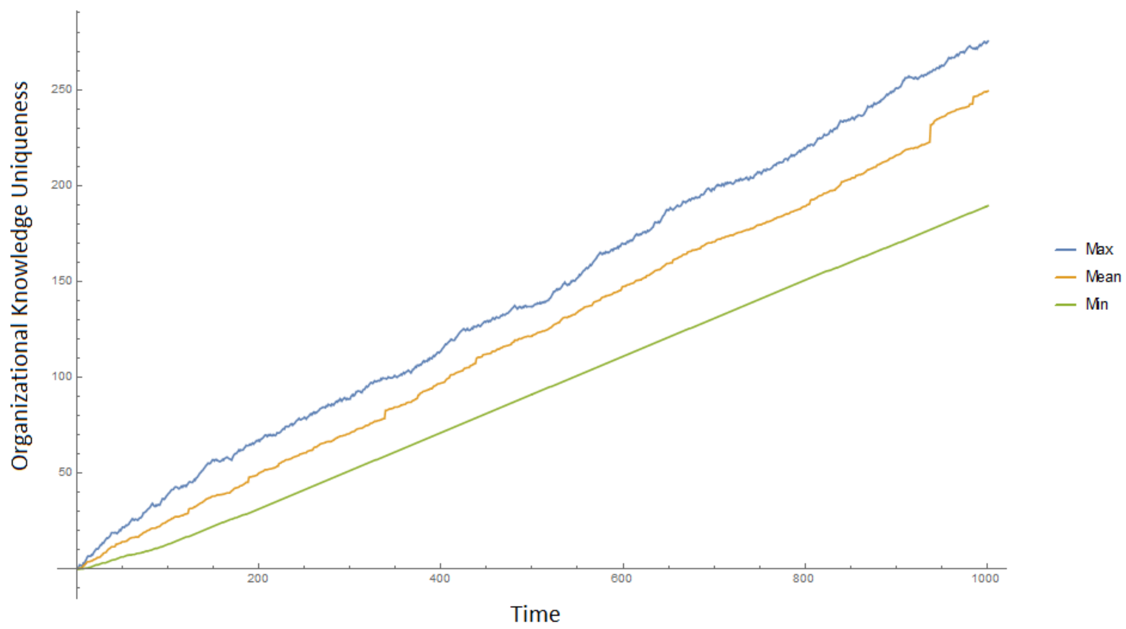

Figure 5-17 Organizational Knowledge Uniqueness in HR Diversity Case

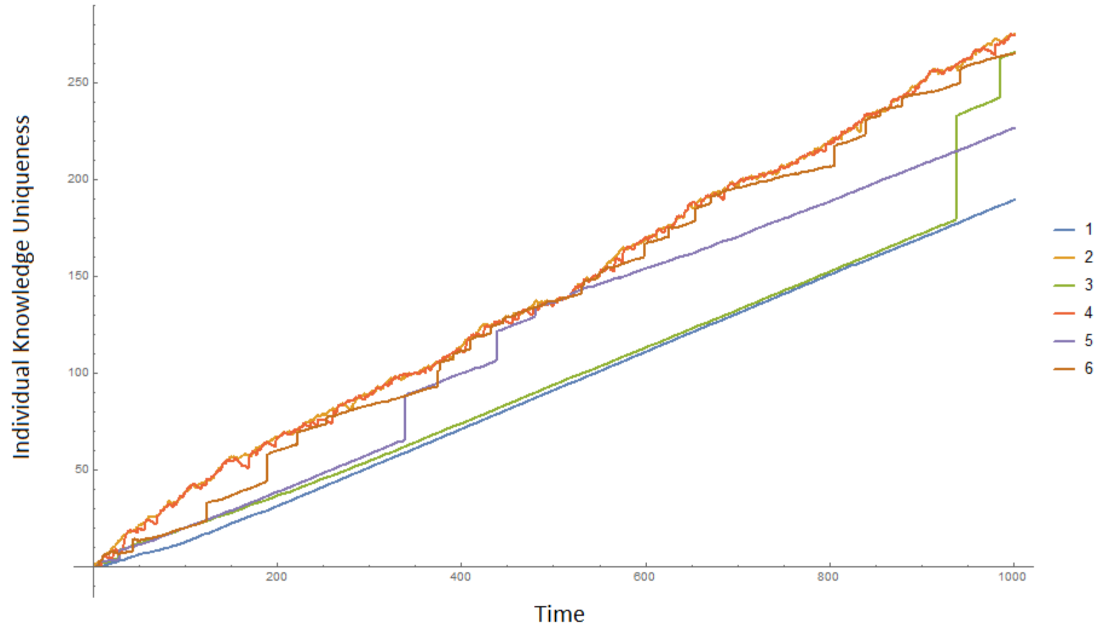

Figure 5-18 Individual Knowledge Uniqueness in HR Diversity Case

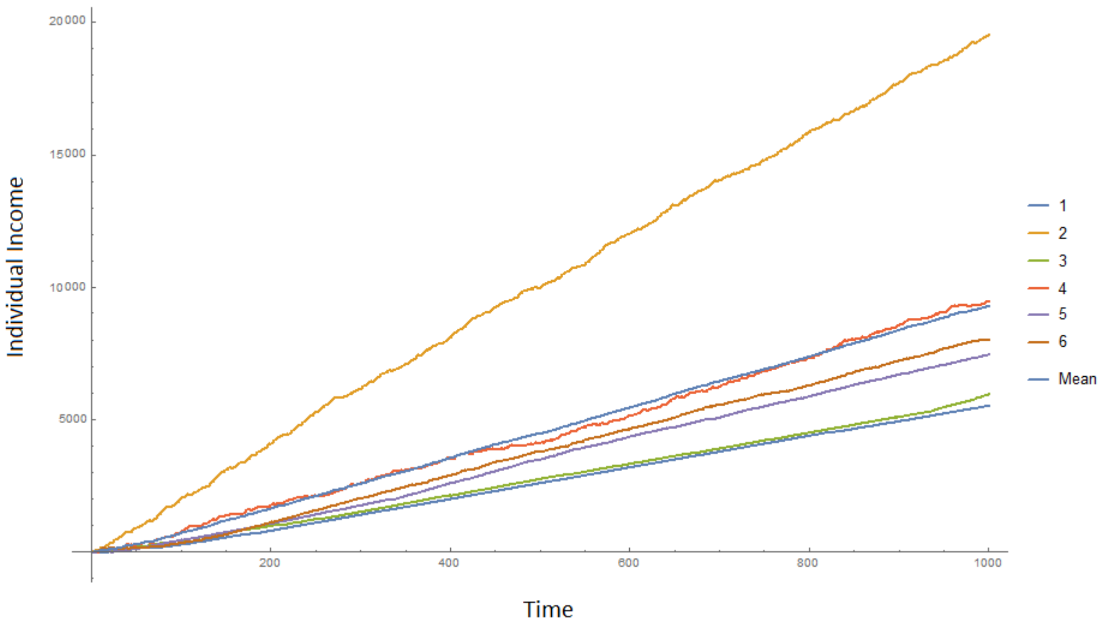

Figure 5-19 Individual Income in HR Diversity Case

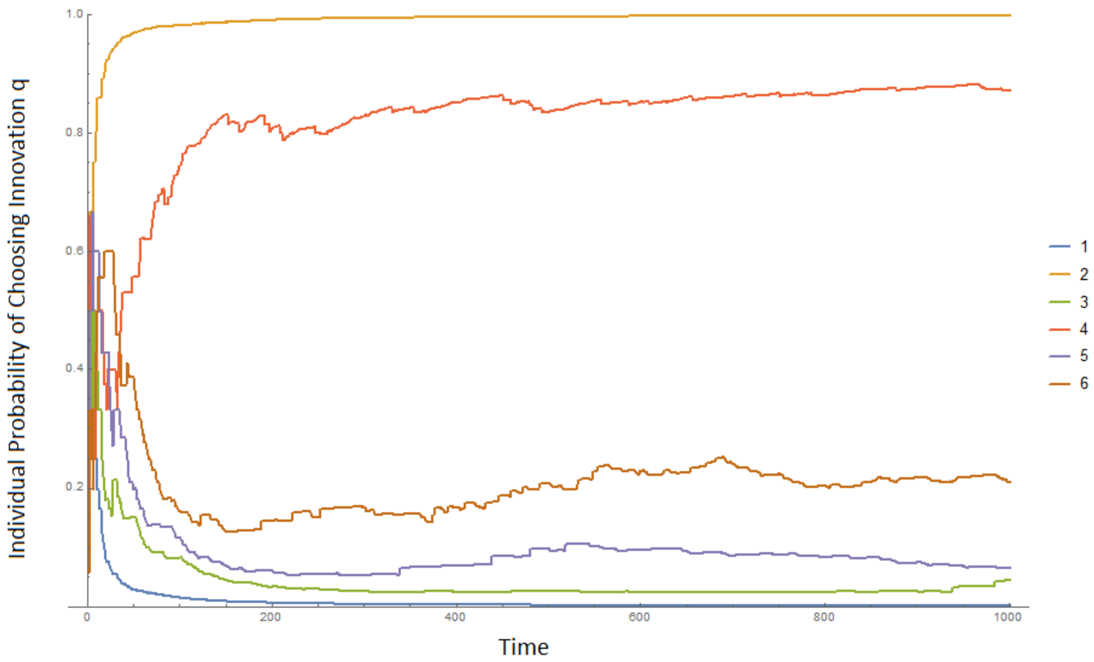

Figure 5-20 Individual Probability of Choosing Innovation in HR Diversity Case

CHAPTER 6 DISCUSSION

This chapter summarizes the findings and discusses the embedded micro-macro links in this study. It further highlights the advantages of the integrated KM methodology, and how it can particularly serve the purpose of coping with growing complexity, environmental uncertainty, human bounded rationality, and incentive system.

6.1 Summary of Findings

Through the development of the basic and extended KM games, this study has made several significant and original findings which include:

(1) It identified a non-monotonicity on macroscopic steady state organizational performance alongside improvement of social network connectivity under turbulent environmental influence, implying that too much knowledge sharing engagement can be harmful for organization when the environment is turbulent.

(2) It revealed a scarcity heuristic decision behavior at microscopic level indicating policy maker at macroscopic level without the consideration of human decision behaviors will not be effective or will have counter-effective outcomes.

(3) An effective incentive system was established successfully. Through the design of knowledge bonus, it wisely links the self-interest agents at the microscopic level to the consideration of organizational benefit at the macroscopic level. Thus, the cooperation arises for gaining indirect benefit.

(4) Social interactions and interdependency were incorporated in all four cases, but it was especially highlighted in reputation building when doing knowledge sharing, implying that too much cooperation can be good for reputation building at microscopic level, but harmful for macroscopic outcomes, then in return, harmful for agents at microscopic level indirectly.

6.2 Micro-Macro Links

The design of the conceptual models in both basic and extended KM game contain key feature that link the micro-macro world. Through the dissertation, the microscopic KM effort impact on macroscopic outcomes are highlighted many times, e.g. the scarcity heuristic decision making found in the basic KM game, which implies that policy without considering microscopic reactions will not work effectively. In this discussion, it is argued that the proposed study not only has bottom-up micro-macro links, but also top-down macro-micro links. The basic KM game studies the environmental influence as the conditions and the heuristics of human agents at microscopic level; whereas the extended KM game centers the macroscopic incentive systems and impact on microscopic social interactions and interdependencies. Moreover, information disclosure of the collective performance is also considered as macro-micro link affecting the decision behavioral of agents at microscopic level.

In the basic KM game, the exogenous administrative policies on productivity of new knowledge μ^{in} and the connectivity of the social network μ^{im} are specified at the macroscopic level for agents to adjust themselves through endogenous adaptation and learning at microscopic level. In the extended KM game, agents at microscopic level behave differently with different incentive interventions specified at macroscopic level. For instance, will the agent chooses innovation more often if knowledge bonus increases, will the agent choose to cooperate with others if his/her knowledge uniqueness is higher than the average, will the agent suffer a little cost to cooperate in the short-run for possibly gaining larger bonus in the long run? These questions can be answered by the KM game. It is argued that these micro-macro two way dynamics can only be caught through the integrated KM approach with ABM simulation and behavioral experiments.

To highlight, in this study, the developed integrated KM approach has demonstrated powerfulness and uniqueness especially in coping with growing complexity and uncertainty as well as building micro-macro links and understandings.

CHAPTER 7 CONCLUSION AND FUTURE RESEARCH

This chapter provides a summary of the achievements through the development of two KM games and implementations in both ABM simulation and behavioral experiments together with the results obtained in the overall study. The significance and contribution of the work to the relevant literature are highlighted. Future work opportunities in the short-run and long-run are suggested.

7.1 Achievements

To summarize, in this study, a basic KM game was designed to achieve the primary goals. An integrated KM methodology combining agent-based simulation and behavioral experiments was developed and verified. The impact of microscopic KM efforts on macroscopic outcomes on organizational performance and structure topology is elucidated. KM policy took consideration of environmental uncertainty and human bounded rationality were evaluated by revealing a steady-state non-monotonicity in organizational performance when enhancing the connectivity of agents and scarcity heuristics for agents' attitude toward more difficult KM strategy. Then additional goals to induce an incentive system and to probe into two dilemmas (loss aversion vs. risk seeking and competition vs. cooperation) on agents' endogenous behaviors against exogenous

KM policy-making has been preliminarily achieved. Furthermore, administrative interventions on promoting innovation, cooperative culture, and diversity have been identified and evaluated. agent-based simulation guided behavioral experiments and expanded the investigation capacities by offering optimization and long-term prediction, whereas behavioral experiments provided model verification and modification with empirical evidence. Such integrated approach demonstrated powerfulness and versatility in explaining various casual relationships, conditions, and effectiveness of interventions.

7.2 Significance and Contributions

Theoretically, this research work is the first of its kind combing agent-based simulation with behavioral experiments in the KM discipline. Methodologically, it offers a powerful and rigorous methodological alternative to cope with growing complexity that conventional approaches are unable to. Practically, it delivers descriptive and prescriptive outcomes including state and dynamics, long term and short term development, evolution and behaviors, etc., for organizational policy-makers to experiment administrative interventions, forecast consequences, generate unforeseeable emergence, and evaluate the managerial effectiveness easily. It serves as a roadmap that make the cause and effect more understandable, hence, new organizational theories can be derived. In summary, this study bridges the theoretical, methodological, and practical gap in the existing literature.

7.3 Future Work

In the future work, short-term and long-term research missions and outlook are suggested. In the short-term, since the extended KM game only gains preliminary results in both behavioral experiments and ABM simulation, more repetition sets of behavior experiments are needed to eliminate the deficiencies, assure the data quality and significance, and the adaptive learning model in the agent-based simulation needs to be more sophisticated utilizing empirical evidence.

In the long-term, the KM game will be further improved by incorporating the freewill, learning, and adaptation of the administrator, hence the co-evolution between the organization and member agents can be realized. Furthermore, the knowledge should enhance agents' cognition, behavior, and performance, meanwhile agents should re-shape, reuse, and renew the knowledge, whereas the organization whether through the administrator or itself should actively adjust the conditions that facilitate the dynamics and growth, so that the co-construction of the reality among knowledge, agents, and the organization will also be possibly achieved. With such an integrated development, the managerial insight can be gained, various causal relations can be sorted, and the effective

KM policies can be designed and tested before execution in the real workplace without sacrificing huge cost or introducing undesired risks.

Ultimately, with the development of sophisticated KM games integrating powerful agent-based simulation and unique behavioral experiments, a new field of study on evolutionary and behavioral KM will be established, theory will be advanced, methodology will be sophisticated, and applications will be abundant.

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APPENDICES

APPENDIX I Pseudo Code of the KM Game

def Agent_Model (i, t):

variable ($\hat{s}_i(t) \in \{0, 1\}^{Hd}$, $\hat{s}_i(t) \equiv \left(\hat{s}_i{}^1(t), \ldots, \hat{s}_i{}^H(t)\right)$ # agent goal

variable $s_i\,(t) \in \{0,1\}^{Hd}$, $s_i\,(t) \equiv \left(s_i{}^1(t), \ldots, s_i{}^H(t)\right)$ # agent solution

vector

Randomly select a task $h \in \{1, \ldots, H\}$

Draw random number 0< r_1<1

if $r_1 < q_i$, *#Innovation is chosen*

Draw random number 0< r_2<1

if $r_2 < \mu^{in}$,

Create new $\boldsymbol{s}'_i(t)$

if $D\left(\boldsymbol{s}'_i(t), \hat{\boldsymbol{s}}_i(t)\right) < D\left(\boldsymbol{s}_i(t), \hat{\boldsymbol{s}}_i(t)\right)$

$\boldsymbol{s}_i(t) \leftarrow \boldsymbol{s}'_i(t)$

In_Success $\leftarrow True$ *#Innovation success*

else

In_Success $\leftarrow False$ *#Innovation failed*

else

In_Success $\leftarrow False$ *#Innovation failed*

if In_Success

$B_i^{in}(t+1) \leftarrow \phi B_i^{in}(t) + 1$

else

$B_i^{in}(t+1) \leftarrow \phi B_i^{in}(t)$

Else *#Imitation is chosen*

Draw random number 0< r_3<1

if $r_3 < \mu^{im}$,

j ←DrawAgent(p_i^j)

$\boldsymbol{s}'_i(t) \leftarrow \boldsymbol{s}_j(t-1)$

if $D\left(\boldsymbol{s}'_i(t),\ \hat{\boldsymbol{s}}_i(t)\right) < D\left(\boldsymbol{s}_i(t),\ \hat{\boldsymbol{s}}_i(t)\right)$

$\boldsymbol{s}_i(t) \leftarrow \boldsymbol{s}'_i(t)$ *#Imitation success*

Im_Success $\leftarrow True$

else

Im_Success $\leftarrow False$ *#Imitation failed*

else

Im_Success $\leftarrow False$ *#Imitation failed*

if Im_Success

$A_i^j(t+1) \leftarrow \phi A_i^j(t) + 1$

$B_i^{im}(t+1) \leftarrow \phi B_i^{im}(t) + 1$

else

$A_i^j(t+1) \leftarrow \phi A_i^j(t)$

$B_i^{im}(t+1) \leftarrow \phi B_i^{im}(t)$

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

$q_i(t) \leftarrow \frac{(B_i^{in}(t))^\lambda}{(B_i^{in}(t))^\lambda + (B_i^{im}(t))^\lambda}$

end

def Initialization[]:

Initialize N agents: $s_i(0), B_i^{in}(0),\ B_i^{im}(0)\ A_i^j(0),\ q_i(0), p_i^j(0)$

def group $\{1, \ \ldots, \ N\} \rightarrow \{1, \ \ldots, \ G\}$

Initialize organization goal scope (U, R)

Initialize group goal (g_k, r) $\in B$(U, R), i=1, $\ldots, \ G$

Initialize $\hat{s}_i(0) \in B(g_{group(k)}$, r), i=1, $\ldots, \ N$

end

def Evaluation(t):

$\pi_i(t) \leftarrow H \cdot d - D(\boldsymbol{s}_i(t),\ \hat{\boldsymbol{s}}_i(t))$ #agent performance

$\bar{\pi}(t) \leftarrow \frac{1}{N}\sum_{i=1}^{N}\pi_i(t)$ # organizational performance

$\bar{q}(t) \leftarrow \frac{1}{N}\sum_{i=1}^{N}q_i(t)$ # organizational decision behavior

$E_i(t) \leftarrow -\sum_{\forall j \neq i} p_i^j(t) \cdot \log_2 p_i^j(t)$ # organizational structure

$$\bar{E}(t) \leftarrow \frac{1}{N}\sum_{i=1}^{N}E_i(t)$$

end

def Environment(t):

Draw random number 0< r_4<1

if $r_4 < \sigma$

$\hat{\boldsymbol{s}}_i\ (t+1) = \hat{\boldsymbol{s}}_i(t)$

else

do

$s'\ (t+1)$ ←Randomly flip 1 to ρ bits

turbulence

while $s'\ (t+1) \notin \bigcap(g_k, r)$

$\hat{\boldsymbol{s}}_i\ (t+1) \leftarrow s'\ (t+1)$

end

```
def Model(parameters…)
        Initialization[]
        for t = 1 to timesteps
          for i =1 to N
                AgentModel(i,t)
          Evaluation(t)
              Environment(t)
end
```

APPENDIX II Behavioral Experiments Results in The Extended KM Game

Game One: Baseline												
Agents						Organization						
	q	Zi	Iin+Iim	Bonus	Income	qbar	Zbar	Pi%	Pi	BonusInput	Coop%	Miu_in
User 1	0.98	0.36	28	81.31	109.31	0.48	0.32	22.67%	208	348.66	36%	0.25
User 2	0.6	0.31	60	63.80	123.80							0.25
User 3	0.16	0.28	76	38.79	114.79							0.25
User 4	0.38	0.34	-76	48.69	-27.31							0.25
User 5	0.48	0.30	28	40.68	68.68							0.25
User 6	0.26	0.33	92	75.39	167.39							0.25

Game Two: Big Bonus												
Agents						Organization						
	q	Zi	Iin+Iim	Bonus	Income	qbar	Zbar	Pi%	Pi	BonusInput	Coop%	Miu_in
User 1	0.26	4.00	116	178.70	294.70	0.52	4.16	29.33%	136	975.50	69.13%	0.25
User 2	0.48	4.13	28	165.81	193.81							0.25
User 3	0.64	4.51	4	204.27	208.27							0.25
User 4	0.62	3.84	36	116.76	152.76							0.25
User 5	0.84	4.30	-92	121.79	29.79							0.25
User 6	0.28	4.17	44	188.15	232.15							0.25

Game Three: Reputation												
Agents						Organization						
	q	Zi	Iin+Iim	Bonus	Income	qbar	Zbar	Pi%	Pi	BonusInput	Coop%	Miu_in
User 1	0.54	-0.25	-60	187.34	127.34	0.46	-0.28	40.67%	160	928.66	94.53%	0.25
User 2	0.3	-0.23	100	179.15	279.15							0.25
User 3	0	-0.36	236	33.73	269.73							0.25
User 4	0.8	-0.23	-68	234.57	166.57							0.25
User 5	0.38	-0.29	76	177.15	253.15							0.25
User 6	0.76	-0.35	-124	116.71	-7.29							0.25

Game Four: HR Diversity												
Agents						Organization						
	q	Zi	Iin+Iim	Bonus	Income	qbar	Zbar	Pi%	Pi	BonusInput	Coop%	Miu_in
User 1	0.52	5.07	60	164.45	224.45	0.64	4.14	59.67%	2552	925.00	94%	0.25
User 2	0.06	0.00	236	0.00	236.00							0.25
User 3	0.56	5.28	244	198.22	442.22							0.5
User 4	1	4.65	460	172.01	632.01							0.5
User 5	0.74	4.93	844	159.89	1003.89							0.75
User 6	0.98	4.89	708	230.44	938.44							0.75