Ph. D. Dissertation in Engineering

A study on knowledge creation in the organization

- focusing on groupthink and collective intelligence aspect

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: 집단사고와 집단지성의 측면에서

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Graduate School of Seoul National University

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- focusing on groupthink and collective intelligence aspects -

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Abstract

A study on knowledge creation in the organization: focusing on groupthink and collective intelligence aspect

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Knowledge is one of the important sources for the progress of mankind. The importance of knowledge has long been emphasized in various fields, and over time independent experts, systems, and studies dealing only with knowledge have emerged. The recent rapid development of technology required more quantity and quality knowledge in our society, and the knowledge became a competitive itself. The old knowledge creation process had highlighted a person's role. In particular, the creation of knowledge by a small group of experts, by excellent individuals, has contributed the most to the production of knowledge. However, the emergence of online spaces due to information and communication technologies and the use of big data have begun to change the human knowledge creation process unprecedentedly.

The production of knowledge based on individual capability gradually began to be replaced

by new technologies and crowds. The combination of new technology proposed a new intellectual system called collective intelligence, which was utilized as the main drivers of decision making and knowledge generation in modern social organizations. However, collective intelligence had some limitations. First, the integration of individual knowledge is difficult because collective intelligence generally represents a high level of decentralization and horizontal hierarchy. A new method of knowledge integration for collective intelligence was required because a simple method of opinion integration, such as the majority rule, could hinder synergetic effects of collective intelligence and could rather result in defective knowledge by groupthink. Another problem is the evaluation of knowledge. The evaluation of knowledge becomes more important when the problem has no single optimal solution. Since an organization without an appropriate level of criticism and evaluation is difficult to produce quality knowledge. That's why different methods are required to evaluate individual and organizational knowledge. In addition, in order to produce knowledge successfully, various conditions must be satisfied. For that reason, most of the prior studies on collective intelligence have focused on the conditions of successful collective intelligence.

What if the conditions of collective intelligence are not satisfied? The answer to this was in the concept of groupthink introduced before the concept of collective intelligence. Groupthink is defined as a group tendency overlooking criticism, evaluation and consideration of alternatives in order to achieve organizational consensus. Groupthink, contrary to collective intelligence, has been pointed out as a source for the failure of organizational decision-making. So, the relevant studies have focused on finding solutions to identify and solve the causes of groupthink in order to prevent organizational fiasco.

The goal of this dissertation is to understand the way for organizational knowledge creation based on two concepts: groupthink and collective intelligence. In order to complete my research goal, three small topics were raised. First, we have to account for groupthink phenomenon which has been the most pervasively used as one of the major sources of group failures. Second, the bridge between groupthink and collective intelligence should be built for finding out the factors enhancing organizational knowledge creation. Third, some strategical aspects are needed. From the self-organization and socio-technological perspective, this dissertation proposes an effective strategy for organizational knowledge creation. The first study in chapter 3 tried to give an answer to the first topic, 'Can we eliminate groupthink from the organization?'. Based on the different perspectives of groupthink proposed in chapter 3, switching factors that transform groupthink into collective intelligence are derived. In chapter 4, we discuss the effect of switching factors and efficient strategies using them. Findings in chapter 4 can give an answer to the question 'Is there any link between groupthink and collective intelligence?'. Chapter 5, the last study of this dissertation, aims to propose effective strategies for the use of technologies such as big data analytics and online platform. More details of each study are shown below.

The first study, "Is groupthink really inevitable?": focusing on the self-organization mechanism", is about the emergent mechanism of groupthink. The study covers two topics in detail. The first is to verify Janis' groupthink model the most well-known. This presented the limitations of Janis' linear model of groupthink and suggested the need for different perspectives. The second was to simulation of groupthink phenomenon occurrence from a self-organization perspective. The results of the simulation experiments showed that groupthink is a phenomenon that can occur naturally in cooperative situations. The findings of this study show that it is more important to make the collective thinking phenomenon productive through appropriate measures than to completely eliminate it from the organization.

The goal of the second study, that is titled "The Optimal Strategy of Organizational Knowledge Creation in Groupthink Situation", is twofold. First, identifying the switching factors for the organization in groupthink to transform into collective intelligence, and secondly, investigating the optimal strategy utilizing the switching factors. In this study, three factors were derived from the previous literature: knowledge conflict, reconsideration of alternatives, and organizational memory. To verify the effects of the three switching factors, an agent-based model simulation was conducted, and the results showed that all switching factors were effective in improving the quality of organizational knowledge, but not in the diversity. In order to derive the optimal strategy based on switching factors, the meta-data of the simulation was used to perform the meta-frontier analysis. The results show that the combination of knowledge conflict and reconsideration has the highest efficiency, whereas the combination of knowledge conflict and organizational knowledge has the lowest efficiency.

The last study, "The effect of the use of emerging technologies on the organizational

knowledge creation: focusing on the use of big data analysis and online platform," identified how the use of new technology affects the production of organizational knowledge. The study focused on the use of big data and the use of online platforms. Based on the survey data, the impacts of the use of each technology on the groupthink and collective intelligence were identified.

Through the above studies, this paper put forward the method of improving the efficiency of the organizational knowledge creation process. Guidelines for establishing organizational strategies using switching factors can be suggested, and the level of use of big data and online platforms can be suggested to encourage collective intelligence.

Keywords: Knowledge management, organization dynamics, collective intelligence, groupthink, agent-based model, socio-technology

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Chapter 1. Introduction

1.1 Research background

Knowledge is becoming a core capability of modern organizations to survive and adapt to the drastic change of environment. In 2016, The fourth industrial revolution made a big wave changing not only industries but also our lifestyles. The essence of the fourth industrial revolution is an era of knowledge through hyper-connectivity, decentralization, sharing, and openness (Schwab, 2017). However, the volume of data and complexity of problems were too high to be utilized by an individual person. People began to depend on the technologies and organizations paid attention to the collective capabilities as a new way how to create organizational knowledge. The number of talented individuals couldn't guarantee a competitive organizational performance anymore.

These social changes brought three challenges for creating new knowledge faster and more effective than before. First, the problems have to be solved are becoming more complex. Most of them include multidisciplinary issues, so they request the cooperation of diverse knowledge domains. Second challenge refers to the amount of knowledge for creating new knowledge. The speed of knowledge accumulation has been increased dramatically with the advancement of ICT. Consequently, the exploding amount of knowledge has prevented that individuals deal with them. Lastly, modern society is increasingly demanding higher level of creativity. Creative idea or knowledge is an important source of innovation and competitiveness because it is still an inherent ability of human beings.

Collective intelligence, introduced to social science by Levy (1994), emerged as one of the most powerful alternative to create the organizational knowledge. On the collective intelligence perspective, well-integrated knowledge shows better performance than simple sum of individual knowledge. However, collective intelligence was not easy to actually utilize. Without appropriate requirements, organizations can induce defective decision makings or knowledge. If an organizational consensus has brought to a fiasco, the organization is likely to be in groupthink phenomenon (I. Janis, 1972). Groupthink is a group tendency to overlook dissent and possible alternatives to pursue an unanimity of organization. This way of thinking decreases the quality of organizational knowledge with several symptoms: overestimation of group, closed-mindedness and uniformity pressures (I. L. Janis, 1982).

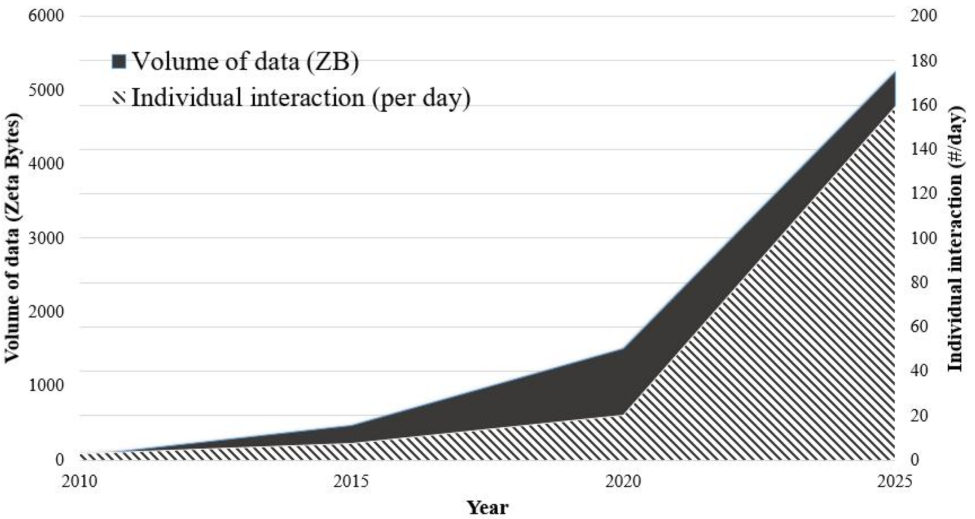


Figure 1. The growth trend in volume of data and interaction in online space[1]

[1] Individual interaction data is from IDC's Data Age 2025 study, April 2017, and Volume of data is from Statista, Volume of data/information created worldwide from 2010 to 2025

1.2 Problem statement

Sometimes, failure of organizational decision making process causes serious damage and casualties. The fall of two space shuttles, Challenger in 1986 and Columbia in 2003, had been considered as man-made disasters. Previous studies pointed out that one major cause of accident was groupthink phenomenon in NASA. This failure led to sequential disposal and suspend of the space development programs, and affected the entire industry of aerospace in USA. In addition, Janis had been argued the existence of groupthink through real world cases such as Vietnam War, Cuba Missile, Korean War and Water Gate and Pearl Harbor.

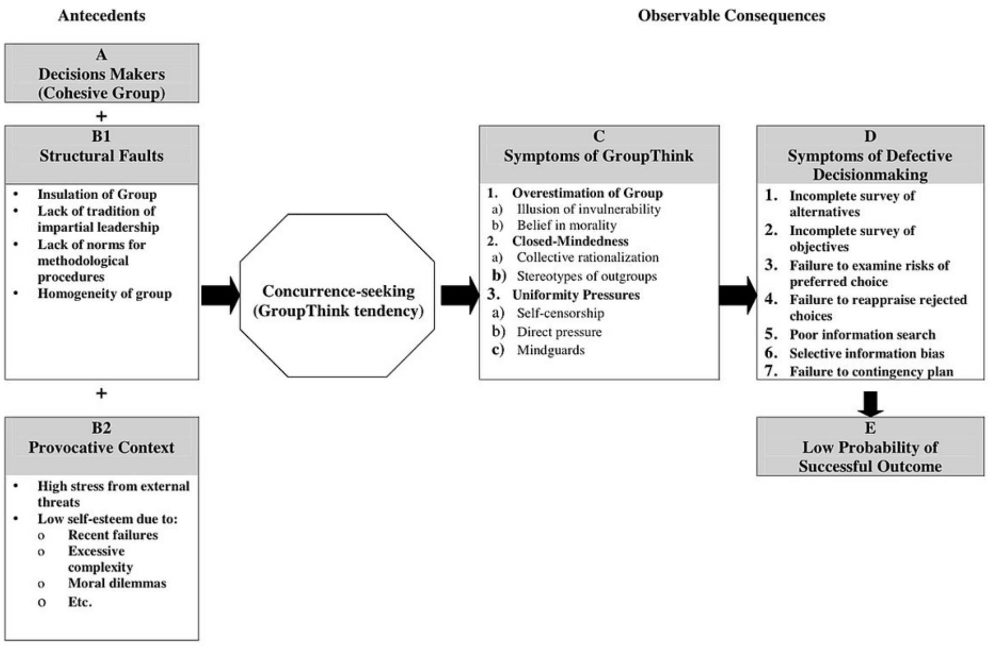


Figure 2. Janis' groupthink model

From the cases of failure in the organizational knowledge creation, previous literature found several antecedents of groupthink. Based on many cases, Janis developed a model to understand why groupthink occurs by four linear causalities as described in figure 1. The follow-up studies have modified his model from various perspectives, for example, self-managing, social identity maintenance, trust, ubiquity model, stress, and etc. Nevertheless, there is little clear evidence or theory to explain groupthink beyond Janis' groupthink model. Collective intelligence and groupthink should be studied if we want to fully use organizational knowledge creation. Since collective intelligence and groupthink shares some common mechanism in their early stage, an organization can control the knowledge process only if be able to understand them. Therefore, this dissertation begins with a question "how can we manipulate knowledge creation of an organization from the perspective of groupthink and collective intelligence?"

1.3 Research objective

The final goal of this dissertation is developing a novel theory for the organizational knowledge creation. In other words, this dissertation deals with the way how to create good organizational knowledge in our organization as efficient as we can. In order to achieve this goal, I designed a research objective structure consisting of 6 small goals, and these goals are grouped by three stages. Each stages are appropriately allocated in the studies of this disseration.

At the first stage, I figured out the mechanism of groupthink on the perspective of self-organization. This is a necessary step to argue that collective intelligence and groupthink are similar intrinsically.

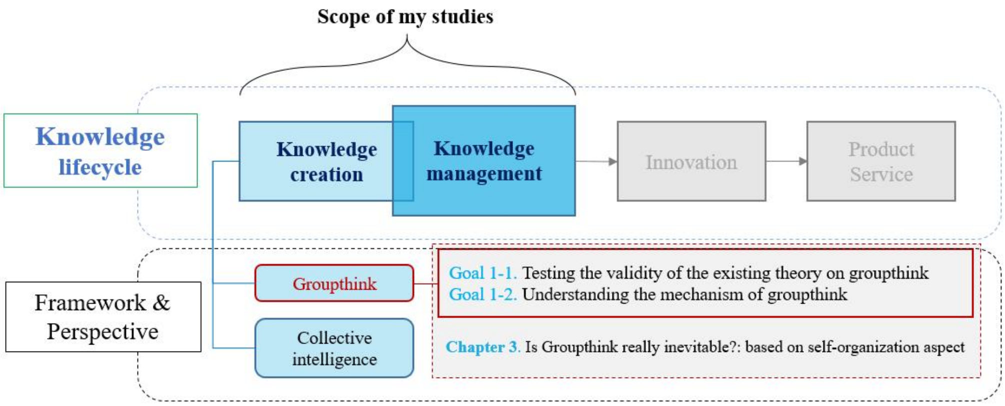


Figure 3. Research objective and position of the first stage

The second stage aims to find out the optimal strategy transforming groupthink into collective intelligence. I introduced the switching factor which is known as common factors enhancing the quality of organizational knowledge and attenuate groupthink phenomenon. Also, this stage provide the options for organizational knowledge creation strategy by comparing the efficiency of strategies including the combination of switching factors.

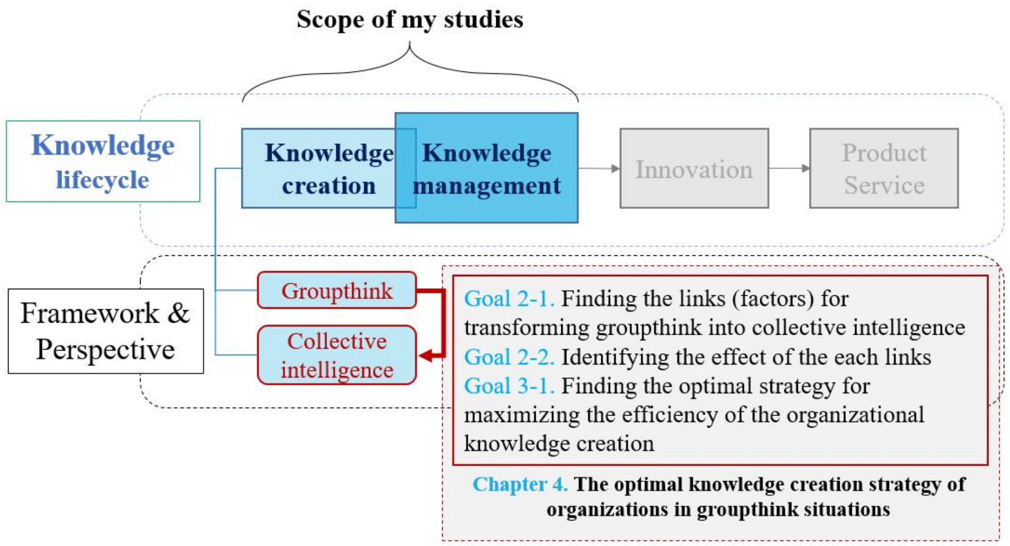


Figure 4. Research objective and position of the second stage

In the last stage, I investigated the effect of not only the use of emerging technologies, but also complexity of organizational tasks influencing on the capability of organizational knowledge creation.

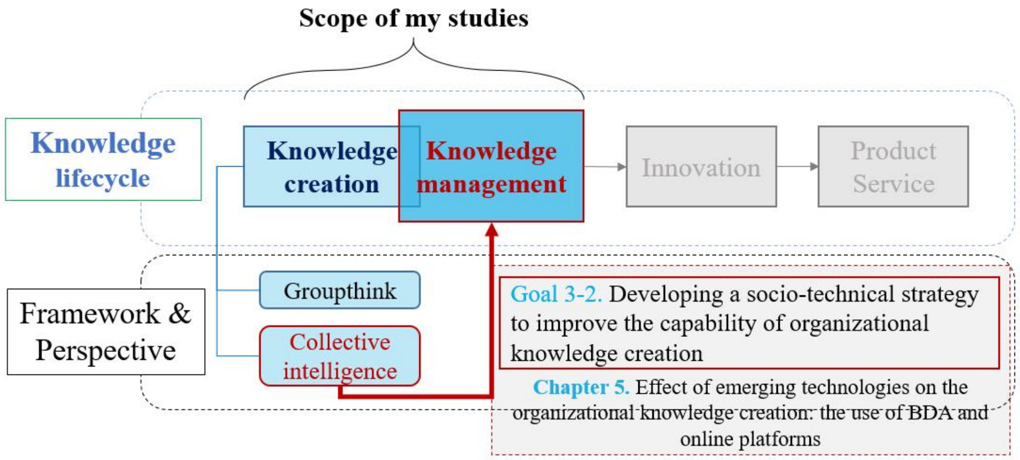


Figure 5. Research objective and position of the third stage

From the conclusions of three steps, this dissertation can contribute to various fields.

Especially, organizations can reduce the cost of knowledge creation because they don't need to concern about resolving groupthink. Also, the contents of the dissertation can be extended to various types of organizations such as firms, R&D institutes, schools, politics.

1.4 Research question

The main question of this dissertation is "How can an organization create the organizational knowledge effectively?". The creation of new knowledge is sometimes essential for organizations to achieve their goals. However, creating organizational knowledge is a very different process from creating knowledge by individuals, so interpretation and framework of knowledge on the level of an organizational is necessary. There are several theories that deal with knowledge from an organizational point of view. The most widely known framework is the resource-based view. From a resource-based view, a new framework that knowledge is regarded as an organizational resource is emerged known as the knowledge-based view. However, in these theories it was difficult to consider the dynamic aspects of the organization, and most studies had emphasized the effective use of knowledge rather than the creation of knowledge. As an alternative to this, the field of knowledge management, which studies the life cycle of knowledge within an organization, has risen rapidly since the 1990s. Knowledge management involves managing the entire life cycle of organizational knowledge by utilizing various interactions, organizational behavior, and systems within the organization. However, the research of knowledge management was still centered on the utilization and value-creating of knowledge. As a result, the creation of organizational knowledge began to extended to the realm of collective intelligence. Collective intelligence has begun to draw spotlights with the development of ICT. Unlike existing organizational knowledge related theories, that focused on the management and utilization of knowledge, collective intelligence clearly focused on the creation of knowledge. Prior to that, in the early 1970s, the concept of groupthink as opposed to collective intelligence first appeared in the field of social science by Irving. Janis. The group thinking theory had been gradually improved through various subsequent studies, but the underlying limitations of Janis groupthink model require the appearance of a new framework. Therefore, in this paper, I will explain the creation of knowledge based on two opposing concepts, collective intelligence and collective thinking research.

In order to give an answer to the main research question, this dissertation organized three detail research questions based on groupthink and collective intelligence theories. Frist, investigation on groupthink phenomenon and the way to deal with groupthink on the perspective of organizational knowledge creation through the question “Can we eliminate groupthink from the organization?”. Based on the answers of that question, I raises the second question “Is there any link between groupthink and collective intelligence?”. To answer this question, I discuss the links between groupthink and collective intelligence, and the meaning of these links. The final question is about the way to enhance the organizational knowledge creation. To finding out those ways, I suggest a question “What kind of strategy is effective to the organizational knowledge creation?”, and try to discover some strategies for improving organizatinal knowledge from the perspecitves of socio-technology and links between groupthink and collective intelligence. The following section describes how each research question is lineked to the three studies of this dissertation.

1.5 Research outline

This dissertation consists of the literature review and three studies. In the literature review chapter, existing theories about knowledge creation, groupthink, collective intelligence, switching factor and emerging technologies influencing on knowledge process. From the chapter 3 to chapter 4 contain the studies on each topic. Chapter 3 is the first study titled “Is groupthink really inevitable?: based on the self-organization aspect”. In this chapter, a different mechanism of groupthink is suggested. Chapter 4 includes a study titled “The optimal knowledge creation strategy of organizations in groupthink situation”. In chapter 4, I investigate the effect of switching factors of groupthink and compare the efficiency of strategies designed by the combination of switching factors. In the chapter 5, the effect of emerging technology on organizational knowledge creation is discussed. The guideline for using information and telecommunication technologies is proposed on the viewpoint of knowledge management. Chapter 6 sums up the content of three studies and delivers organized conclusions.

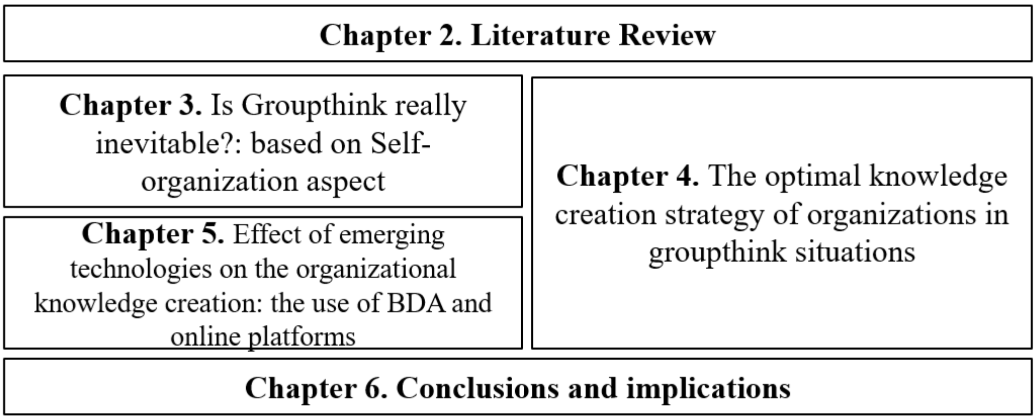


Figure 6. Outline of dissertation

Through this dissertation, I am expecting that there will be three major contributions. First, this dissertation can provide a new point of view for handling groupthink phenomenon. In old perspective, groupthink is a fiascoes exacerbating group decision making process and quality of outcome. However, actually it is very natural, because groupthink is a stage to go to the collective intelligence. So, it is better to transform groupthink into collective intelligence than just inhibit it. Second, a systemic and behavioral approach to emerge collective intelligence can be given. Previous studies have approached creating collective intelligence through developing systems such as information collecting, integration, and feedback. Different from this, our study emphasizes the behavioral aspect of group members. So, this point can contribute to the organizations which hard to adopt the CI systems. Third, this dissertation will supply evidence to determine the use of emerging technologies for effective organizational knowledge creation, such as big data analytics and online platforms. Technology has been considered as an effective way to increase organizational knowledge. However, this study will suggest an opposite idea that the extreme dependency on them can ruin the knowledge of an organization. In other words, a balance between technology and human is necessary for making a better organizational knowledge.

Chapter 2. Literature review

2.1 Creation of organizational knowledge

Organizational knowledge is defined as a complex of individual knowledge (Davenport & Prusak, 1998). However, organizational knowledge is distinguished from a bundle of knowledge on the aspect of its synergetic convergence. That's why the organizational knowledge needs to be managed by a specific process involving the members, culture and technology (S. Kim & Kim, 2000).

The most basic way to produce a new knowledge is to depend on the talanted individual's capability. Knoweldge creation by experts focused on strategic knowledge because this method is not a systemic process (Gruber, 1989). Also, for reasons of cost and time, not all knowledge created by individuals in the organization can be shared; too much redundancy in knowledge offsets the advantages of specialization and division of labour (Grant, 1996). Another static view of knowledge creation stemmed from the resource-based view. From this perspective, organizations seek to acquire resources from the environment (Porter, 1980). Thus the studies on the resource-based view emphasized the strategies how firms make and keep their competitive resources under the uncertain environment. However, empirical and theoretical studies of this viewpoint had focused on how to keep and exploit competitive resources rather than how to create them (Amit & Schoemaker, 1993; Barney, 1991; Dierickx & Cool, 1989; Peteraf, 1993; Wernerfelt, 1984). Although the resource-based view is rooted on the dynamic capability of firm (D. Teece, 1990), it failed to explain the dynamism in organizations such as interactions among their resources (Nonaka & Toyama, 2003).

Because of the special characteristics of knowledge, the resource-based view extended to the knowledge-based view (e.g., Barney, 1991; Chen & Edgington., 2005; Kogut & Zander, 1992; Wernerfelt, 1984). The knowledge-based view argues that the organizational knowledge can give rise to the competitive advantage and fulfilling diverse and many demands (Ikujiro Nonaka, Von Krogh, & Voelpel, 2006a). In other words, if an organization chases profit maximization, it cannot overcome the idiosyncrasy of organizational knowledge creation and acquire competitive advantages differentiating them from the others. Knowledge management was developed to support the compeitive achieving the competitive advantage (Van Reijsen, Helms, Batenburg, & Foorthuis, 2015) through organizational knowledge creation, processing, storing, distributing and utilization (Pan & Scarbrough, 1999). The early knowledge management system were often equated with the information process system (Alavi & Leidner, 2001), but the recent studies on the knowledge management have focused on knowledge collaboration.

Collective intelligence is a viewpoint that more emphasizes the spontaneous emergence of knowledge than either the knowledge management or the knowledge-based perspectives. Collective intelligence is often confused with wisdoms of crowds or swarm intelligence, but collective intelligence is more intellectual and synergetic actions of the organization (Atlee, 2003; P. Levy, 1994; Tapscott & Williams, 2006). Also, collective intelligence focuses on organizational knowledge creation and knowledge itself (J. H. Lee & Chang, 2010). The special charateristics of collective intelligence provide the different strategiese for organizatinal knowledge creation. Since collective intelligence is an extension of the wisdom of crowd, collective intelligence inherently includes the properties of wisdom of crowds as shows in the table 1. From the perspective of user participation, Musser & O'reilly (2007) and Needleman (2007) argued that enhancing participation by accessibility toward the database and network can lead to collective intelligence. Integration of dispersed knowledge has been continously adopted as one of the essential factor of organizational knowledge creation (Spielman, 2014a; Surowiecki, 2004) through collective intelligenec (Lopez Flores, Belaud, Le Lann, & Negny, 2015; Mallewong & Wowongse, 2008). In addition, Woolley et al (2010) and Engel et al. (2014) suggested conflicted evidence on what drives collective intelligence as a group capability. According to that study, interactions based on the social sensitivty and diversity are main source of collective intelligence.

Table 1. Comparison of collective intelligence and wisdom of crowds

	Collective intelligence	**Wisdom of Crowds**
Similarity	· Decentralized participation · Accuracy controlled by the volume of data · Emphasis on information aggregation mechanism	
Purpose	Knowledge creation	Problem solving
Methodology	Abstraction and enhancement	Social proofing
Individual	High degree of interactivity	Insolated group
Case	Wikipedia, GitHub, Stack overflow, etc.	Recommendation system, election, commentary, etc.

2.2 Groupthink

The first groupthink model Janis (1972) proposed six cases which are known as victims of groupthink. In his study, the antecedents, symptoms, defective decision making process, and quality of decision making which is the result of previous three factors were connected serially. The term of groupthink was firstly introduced by Janis (1972) . In Janis (1972), groupthink was defiend as *"The mode of thinking that group members engage in when they are dominated by the concurrence-seeking tendency when their strivings for unanimity override their motivation to appraise the consequence of their actions"*. In the first study of groupthink, six cases consiting of two nongrouopthink cases and four groupthink cases were used for explaning the existence of groupthink in each case.

Table 2. Groupthink and non-groupthink cases

Reference	Non-groupthink cases	Groupthink cases
Janis (1972)	Marshall Plan, Cuba Missile Crisis	Pearl Harbor, Korean War, Bay of Pig, Vietnam War
Raven (1974)	-	Water Gate
Huseman & Driver (1979)	-	Fixed price system in electricity market
Tetlock (1979)	Vietnam War	-
Smith (1984)	-	Iran hostage rescue
Hensley & Griffin (1986)	-	Constructing an auditorium in Kent
Esser & Lindoerfer (1989)	-	Challenger space shuttle (STS-51-L)
Moorhead,		

Ference, & Neck (1991)		
Sims (1992)	Beech-Nut, E.F. Hutton, Salomon Brothers	-

After 1972, the groupthink model was updated by various methods in interdisciplinary studies. Janis (1972) presented six well-known cases as evidence in the first groupthink model. He assumed that seven antecedents induced concurrence-seeking which brought about the groupthink phenomenon and the negative effect of groupthink on the quality of organizational decision-making. In this framework, the original groupthink model emphasized the concurrence-seeking tendency as a critical source of groupthink (Rajakumar, 2019). Janis' groupthink model was settled as one of the effective methods to understand defective or premature organizational decision-making (e.g. Esser and Lindoerfer, 1989; Manz and Henry P. Sims, 1982; Park, 1990; Peterson et al., 1998; Raven, 1998)

Studies that tested causalities in Janis' groupthink model presented contradictory results (Paul't Hart, 1991). Group cohesiveness, which was opposed to Janis (1972), turned out to attenuate groupthink tendency (Courtright, 1978; Flowers, 1977). These contradictory results began to raise doubts around the validity of Janis' model. Thus, subsequent literature began to focus on reducing the gap between theory and the real world by suggesting various theoretical alternatives. For example, political property (Paul 't Hart, 1998; Kramer, 1998), social identity (Alvaro & Crano, 1996; David and Turner, 1996; Turner and Pratkanis, 1998a), compliance and internalization (McCauley, 1989), group efficacy (Whyte, 1998), self-adjustment (Flippen, 1999), anxiety (Chapman, 2006), pluralistic ignorance (Packer, 2009), and trust (Erdem, 2003) were proposed to enhance the explanatory power of the existing groupthink model. Furthermore, there were some studies that emphasized that the combination of specific contexts and groupthink antecedents may lead to a groupthink tendency (e.g. Chapman, 2006; McCauley, 1989; Mok and Morris, 2010). In more recent studies, the relationship between groupthink and task characteristics (Brockman, Rawlston, Jones, & Halstead, 2010; McAvoy & Butler, 2009), groupthink in the online community (Breitsohl, Wilcox-Jones, & Harris, 2015; Størseth, 2018), and temporary groups (Hällgren, 2010; Lindkvis, 2005) have been considered to expand the scope of the groupthink theory. However, despite a number of studies in the literature including case studies, empirical analysis has provided only fragmented evidence of Janis' groupthink model (J. Esser, 1998). The groupthink studies only supported the part of Janis' groupthink model (Herek, Janis, & Huth, 1987; Leana, 1985), and the results were contradictory to the Janis' groupthink model (Sniezek, 1992). According to these studies, excessive concurrence-seeking tendencies and inferior decision-making as a result of groupthink could not be explained sufficiently by Janis' model (G Moorhead, Neck, & West, 1998; W. Park, 1990; Turner & Pratkanis, 1998c). Contrary to case studies, empirical studies argued that cohesiveness had little or no effect on the emergence of groupthink (e.g. Flowers, 1977; Fodor and Smith, 1982; Hart, 1991; Miranda and Saunders, 1995; Park, 2000). Thus, the lack of empirical evidence and the ignorance of dynamic perspectives were proposed as fundamental reasons contributing to the theoretical dilemma in Janis' groupthink framework (Greenwald &

Ronis, 1978). As a result, regardless of the theoretical attempt to combine with a different field, it was tough to explain the whole groupthink model (G Moorhead et al., 1998; W. Park, 1990; Turner & Pratkanis, 1998c). Especially, the quantitative analyses attenuated the causality between the group cohesiveness and groupthink symptoms which is the key assumption of Janis' model (e.g., Flowers, 1977; Fodor and Smith, 1982; Hart, 1991; Miranda and Saunders, 1995; Park, 2000). Then, what is the main defect of Janis' groupthink model? Previous studies had pointed out two potential causes that bring the insufficiency of the linear groupthink model: lack of evidence and dynamic perspective.

2.2.1 Criticisms on empirical evidence

The case study method was a major approach relied on in groupthink research. The first groupthink study (Janis, 1972) used six real-world events such as Pearl Harbor and the Vietnam war. Thus, all the studies that followed also focused on real-world cases. However, the cases adopted in groupthink research only included those that involved failed decisions or hierarchical organizations such as military or political groups (Riccobono, Bruccoleri, & Größler, 2016). The narrow spectrum of cases led to empirical research providing measurable evidence based on laboratory experiments, surveys, or interviews.

Several obstacles hindered attempts at empirical analyses of Janis' groupthink model. The popularity of Janis' model, problems such as abstruseness of measurement and conceptual ambiguity (Turner & Pratkanis, 1998c), difficulties in making observations around groupthink symptoms (W. Park, 1990), and the self-objectification of the respondents (J.

Esser, 1998) made the empirical analysis inconsistent (Rajakumar, 2019). Notably, the two essential causalities of Janis' model have not been shown in previous empirical studies (Longley, J., & Pruitt, 1980). Further, there was no consideration of any of the other factors that determined the groupthink phenomenon. Thus, the relationship between the antecedents and groupthink became exclusive. These problems can still be found in recent studies on groupthink (e.g. Lee et al., 2016; Størseth, 2018).

2.2.2 Criticisms on framework

Since Janis' model was established on the top-down and static framework, most studies also have depended on the top-down perspective. The top-down approach assumes that relational, structural, and environmental factors involved in an organization are able to manipulate organizational and individual behaviors. However, since various traits and behaviors of an individual member should be considered in the analysis of the emergent phenomenon, Hart (1991) argued that the groupthink phenomenon can be one of the results produced by interactive behaviors among group members. The lack of a dynamic perspective in groupthink research has also been criticized (McCauley, 1998; Riccobono et al., 2016). There has been little research on adopting a dynamic aspect in Janis' groupthink model. Indeed, adopting a dynamic aspect is challenging work in the groupthink context because it comes in conflict with Janis' model, which is most pervasively used. Therefore, the organization dynamics has been treated as a trivial aspect in Janis' groupthink framework (Whyte, 1998).

In response to the criticism mentioned above, three major streams of literature appeared (Turner & Pratkanis, 1998c). First, the most radical group insisted on the entire replacement of the existing model. In reality, it is difficult to find a source for the discordance of these empirical studies. Thus, the possibility of external factors cannot be excluded. Since limited and ambiguous evidence cancelled out the benefits of the existing theory (Aldag and Riggs Fuller, 1998), the value of Janis' model decreased further. Thus, the group that was skeptical of Janis' model began to emphasize an alternative theory that was totally different from the existing model (Chen, C. K., Tsai, C. H., & Shu, 2009; Park, 2000). Consequently, groupthink studies began to expand into fields like collective and swarm intelligence in order to overcome the limitations inherent in the existing model. This study belongs to here.
The second group took a moderate stance toward Janis' model. They tried to enhance the usefulness of the model by reorganizing the factors and their relationships (Chen,, Tsai, & Shu, 2009) while maintaining the framework of the existing model as far as possible. Studies in this stream considered various aspects such as the maintenance of social identity (Turner & Pratkanis, 1998a), self-regulatory theory (Flippen, 1999), trust and distrust (Erdem, 2003), ubiquity model (Baron, 2005), the spiral of silence (Packer, 2009), and deliberate ignorance (Bénabou, 2013), among others.

Different from the previous streams, the third perspective pursued another means to enhance the value of Janis' groupthink model. Contrary to that, the previous two groups began to emphasize the explanatory power of the model, particularly the practical aspects (Bénabou, 2013; Hällgren, 2010; Paul't Hart, 1991; Manz & Henry P. Sims, 1982; Pidgeon

& O’Leary, 2000)

Table 3. Three types of responses of Janis’s groupthink model

Reorganization of Janis′ groupthink model	Janis(1972)	Original model of the groupthink model
	Flower (1977)	Insignificant effect of group cohesiveness
	Courtright (1978)	Effect of interaction among the group members
	Manz and Sims(1982)	Groupthink in the autonomous work group
	Callaway, Marriot and Esser (1985)	The influence of social dominance on the groupthink
	McCauley(1989)	Two type of group cohesiveness
	Neck and Manz (1994)	Transform the groupthink into the team think
	Mullen, Anthony, Salas and Driskell (1994)	The effect of group size and cohesiveness on the groupthink phenomenon
	Turner and Pratkanis (1998b)	The relationship between social identity maintenance and groupthink
	Whyte (1998)	The effect of group efficacy on the groupthink
	Kramer (1998)	The effect of political factors on the groupthink
	Erdem and Ferda (2003)	Influence of the internal trust on the groupthink
	Baron (2005)	Suggesting ′Ubiquity groupthink model′
	Chapman (2006)	The relationship between organizational anxiety and the groupthink
	Packer (2009)	Applying ′spiral of silence theory′ into the groupthink model
Practicalismic approaches	Pidgeon&O′Leary (2000)	Practical use of the groupthink theory in the disaster control
	Benabou (2013)	Preventing the collective ignorance and delusion in the market through the groupthink theory
	Tennant (2011)	Inefficient decision-making in the urgent situation
	Burdon et al. (2016)	Explanation of ethical compliance through the groupthink theory
Alternative approaches	Surowiecki (2004)	Collective intelligence in the social context
	Mok & Morris (2010)	Emergence of groupthink through the bicultural identity conflict
	Lee & Chang (2010)	Creative evolution system
	Prindle & Hasty (2010)	Stochastic emergence of groupthink in social amoeba
	Yong Tao (2018)	Swarm intelligence in human society

2.3 Collective intelligence

Collective intelligence is a fancy word to describe the self-organized knowledge, which is defined as the intellect exist everywhere, is contantly valued, is coordinated in real-time, and can be utilzied as a practical ability (P. Levy, 1994). On the practical perspective, it can be also defined as a genearl capability of an organization applied in various tasks (Woolley et al., 2010). The essnece of collective intelligencce in that collective intelligence is much larger than the sum of individual knowledge (Maleewong, Anutariya, & Wuwongse, 2008; Surowiecki, 2004; Yun & Lee, 2011). The special charateristics of collective intelligence have raised the demand for alternative mechanisms of organizational knoweldge creation.

The first concept of collective intelligence was presented by William Morton Wheeler in biology area. In 1983, Peter Russel suggested a sociological definition of the collective intelligence. Finally, Levy (1994) presented the collective intelligence on the online space and this concept have been used pervasively until now. Although the exact concept of collective intelligence is still in controversial (see table 5), they have shared the central value of collective intelligence: decentralization and collaboration.

With an increase of attention toward collective intelligence on the perspective of organizational competence, relevant studies have been conducted to find out the source of collective intelligence. Previous literature has suggested multiple factors determining the level of collective intelligence. Individual intelligence was an expected factor determining the level of collective intelligence. Bates and Gupta (2017) argued that the individual intelligence defines the level of collective intelligence. On the other hand, some studies presented the empirical evidence supporting the independence between the individual intelligence and collective intelligence (Curşeu, Jansen, & Chappin, 2013; Engel et al., 2014; A. W. Woolley et al., 2010; Anita Williams Woolley, Aggarwal, & Malone, 2015). Especially, Woolley et al. (2010) argued that social sensitivity and organizational diversity are essential determinants for the level of collective intelligence rather than individual abilities such as IQ. In the moderate group accepting both sides of studies, multiple variables involving the individual intelligence, diversity were revealed as key determinants influencing on the level of collective intelligence (Devine & Philips, 2001; Ellis et al., 2003; LePine, 2005).

In addition, collective intelligence is related to the development of information communication technology (ICT) (P. Levy, 1994; Lopez Flores, Negny, Belaud, & Le Lann, 2015; Täuscher, 2017). Since ICT widened the scope of communication, people have been exposed to a larger amount of knowledge through knowledge transfer, sharing, recombination (Robertson et al., 1996). Recently, artificial intelligence(AI) technology has deepened the human perception of the real world. The combination of ICT and AI technology helps an organization solving problems using collective intelligence at a lower cost than before.

A variety of researches have described the collective intelligence in organizations. The first stream of research is in ecology investigating the collective intelligence phenomenon of animal communities (Hofstadter & Gödel, Escher, 1979; Prindle & Hasty, 2010; L.

Thomas, 1974). Also, collective intelligence has been considered as an important issue in human society. Despite the early studies focused on conceptual description or specific relationship that people may face (D. Weschsler, 1971; Gregg, 2009; M. Bruch, E. Bodden, 2010). However, after this context, several studies presented emergence of collective intelligence in terms of either complex adaptive system (e.g., Madureira, Pereira, Pereira, & Abraham, 2014; Furtado et al., 2010; S.-K, Chai, Mabry, Stiles, & X. Cui, 2010) or social network (e.g., Chaves, Steinmacher, & Vieira, 2011; Gholami & Safavi, 2010; Morge, 2005; A. Pentland, 2007). However, they have a little bit different focus toward collective intelligence.

Collective intelligence studies emphasizing social network perspective showed more interest in the diffusion of knowledge or knowledge transfer (Broekel, Balland, Burger, & van Oort, 2014; Sohn, 2014). Also, some studies tried to figure out the relationship between the characteristics of network (e.g., links, centrality, structure, etc.) and their knowledge or intelligence performance (Enemark, McCubbins, & Weller, 2014; Espinosa & Clark, 2014; Rodan & Galunic, 2004).

Different with that, the studies on complex adaptive aspect of collective intelligence emphasize the emergence or representation of collective intelligence. In other words, since they focused on how to integrate or aggregate individual knowleldge effectively, interactive bahavior of people is considered as a more crucial factor (e.g., Engel et al., 2015; Liegl, 2014; Rosenberg, 2015; Toyokawa, Kim, & Kameda, 2014; Anita Williams Woolley, Aggarwal, & Malone, 2015). Thus, this study took a stance of later perspective because this study will concentrate on the behaviors of individuals rather than network topology or degree.

Recently, collective intelligence emerged as an effective way not only to create knowledge for the complex social problem (McHugh et al., 2016) but also to be a core competency of firm's knowledge management (Ahn & Lee, 2009) because collective intelligence has two advantages as a competence of an organization. First, when collective intelligence exists in the group, in the general cases, the quality of group decision is superior to the individual's one. In other words, collective intelligence makes a group smarter through interactions, integration and evalution rather than talented people. As the evidence of this, previous studies found that the intellectual ability of group member is likely to be irrelevant to the level of collective intelligence (Curşeu et al., 2013; Engel et al., 2014; A. W. Woolley et al., 2010; Anita Williams Woolley et al., 2015). Second, collective intelligence is likely to expand the scope of the capability of a group. It is easy to draw an interdisciplinary knowledge when collective intelligence operates well. That's why decentralizaiton and diversity are important factors for collective intelligence.

Table 4. Concepts of collective intelligence

	Levy (1994)	Surowiecki (2004)	Tapscott & Williams (2006)	Leadbeater (2008)	Bruns (2008)
Characteristics	Diversity Identity	Diversity Autonomy	Openness	Participation	Open participation
Motivation	Recognition of identity	-	-	Recognition of contribution	Social recognition, Social capital
Interaction	Real-time adjustment	Autonomous adjustment and practice	Sharing	Contribution and recognition Relationship	Common evaluation Steady improvement
Organization	Fair evaluation and valuation	Self-organization Decentralized adaptability	Equal production Self-organization	Core group Cooperation Auto-regulation and creativity	Adaptive complex order Ex-post ability system
Differentiation	Focusing on macroscopic view of civilization history	Emphasizing wisdom of crowd	Collective intelligence in firm level	Basis on Web and communalism	Focusing on Web based information goods and service production

2.4 Switching factors

Previous studies have tried to figure out the links between groupthink and collective intelligence in various ways. Solomon (2006) argued that groupthink can be transformed into wisdom of crowd when two conditions are satisfied. He suggested organizational diversity and decentralization for prevent the 'tipping point' of groupthink. However, this study is a conceptual paper, so detail investigation was required to understanding the mechanism of interconversion between groupthink and collective intelligence. In this context, several studies have proposed a plausible idea about interconversion between two concepts. Erdem (2003) brought the concept of trust to explain why distrust group can have higher the organizational performance than trust ones. In that study, excessive mutual trust increases groupthink and decrease teamthink. Contrary to that, appropriate level of trust can be better. Reia et al. (2019) proposed that the way to collaboration can determine whether an organization falls into groupthink or developing collective intelligence. According to their study, sharing limited knowledge is likely to induce collective intelligence rather than sharing whole knowledge. In addition, Jafari et al.(2015) conducted a social experiment on the virtual space. From the result of their study, two aspects were raised as determinants where an organization will go groupthink or collective intelligence: diversity and creativity.

Table 5. Comparison of groupthink and collective intelligence

	Groupthink	Collective intelligence

Definition	The trend of an organization or mindset ignoring the exploration of alternatives and evaluation to achieve unanimous knowledge (I. L. Janis, 1982)	An intelligence that exists everywhere and is consistently valued and coordinated, and can be utilized as a practical capability of an organization (P. Levy, 1994)
Purpose	Decision making, knowledge production, problem solving	Decision making, knowledge production, problem solving, abstraction and enhancement
Framework	A set of linear causalities	Emergence, Complex adaptive system
Theory	Janis groupthink model	Various hypotheses (e.g., Levy, Surowiecki, Dutton)
Motivation	Cohesiveness, structural faults, provocative context	Social identity, social recognition, social capital, etc.
Cases	Vietnam War, Water gate, Pig bay, Cuba missile, Korean War, Pearl bay, etc.	Wikipedia, GitHub, Stack Overflow, etc.
Medium	Concurrence seeking, uniformity pressure, Leadership, etc.	Interactions, sharing, integrating, filtering, evaluating, etc.
Solutions	Conflict, equal authority, evaluation, diversity, reconsideration, external resource, contingency plan, storing and retrieval (organizational memory), supportive leadership, etc. (e.g., Janis, 1982; Riccobono et al., 2016;McCauley, 1989; Flippen, 1999)	Knowledge conflict, knowledge collaboration, knowledge archive, integration, evaluation and filtering, independency, diversity, decentralization, equality, openness, sharing, IQ, social sensitivity (e.g., Woolley et al., 2010; Spielman, 2014; Hwang et al., 2009)

When groupthink changes to collective intelligence, the main problem is how to realize this change. As mentioned above, groupthink and collective intelligence have similarities in their perspectives on mechanism. Thus, we hypothesized that the intersections between the two phenomena could be a source of interconnection. So, switching factor is defined as an essential determinant that transform the organization in groupthink situation into the organization with collective intelligence. The previous studies on groupthink and collective intelligence presented three common factors in preventing groupthink and promoting collective intelligence. In this study, swithching factors are selected by these intersection between the groupthink solutions and the determinants of collective intelligence proposed in the previous studies.

Table 6. Switching factor as an intersection of groupthink and collective intelligence

	Solution for groupthink	Determinant of collective intelligence
Knowledge conflict	Ferraris & Carveth (2003), Flippen (1999), Gully, Devine, & Whtney (1995), I. L. Janis (1982), Massari et al. (2019), Packer (2009), Solomon (2006), Sunstein (2005), Turner & Pratkanis (1998a)	Chiocchio, Forgues, Paradis, & Iordanova, (2011), Hartwick, J. & Barki (1994), Malone & Bernstein (2015)
Reconsideration of alternatives	Chapman (2006), Ferraris & Carveth (2003), Flippen(1999), I. L. Janis (1982), I. L. Janis & Mann (1977), Park (2000), Riccobono et al. (2016), Turner & Pratkanis (1998a)	De Vincenzo, Massari, Giannoccaro, Carbone, & Grigolini (2018), Golkar (2013), JafariNaimi & Meyers (2015), Loasby (2002), Maciuliene & Skarzauskiene (2016), Solomon (2006), Spielman (2014), Anita Williams Woolley et al. (2015)
Organizational memory	Casey-Campbell & Marten (2009), Reaves (2018), Barki & Hartwick (2004)	Bieber et al. (2002), Hinsz, Vollrath, & Tindale (1997), Reia et al.(2019), Solé et al. (2016)

2.4.1 Knowledge conflict

The first factor is “organizational conflict.” When multiple knowledge exists in an organization, people evaluate each knowledge based on their own background (Heit & Bott, 2000) or prior experience in organization (Allee, 2012). Existing knowledge can be replaced by new alternatives through social collaboration and individual cognition (Ikujiro

Nonaka, 1994; B. T. Pentland, 1995). This denotes that not only individual differences but also interactions are necessary to create organizational knowledge. In other words, an organization requires a compound of cooperation and competition called "coopetition" (Gast, Gundolf, Harms, & Matos Collado, 2019). Organizational conflict is a superficial output manifested by "coopetition."

Organizational conflict occurs through heterogeneous perspectives during the decision-making process (Karen A. Jehn & Mannix, 2001). Previous studies classified organizational conflict into "task conflict" and "relational conflict."(Jehn and Mannix, 2001; Amason, 1997; Hon, 2007; Jehn, 1995). Both types of conflict are able to aggravate organizational performance if there was no appropriate management (Allen C. Amason, 1996; Hambrick, Cho, & Chen, 1996). Organizational conflict is not just one of the major factors enhancing organizational performance (e.g., Deutsch, 2000; Greenhalgh, 1987; Pondy, 1967; Robey et al., 1989), it also brings the cognitive growth of group members (Ames & Murray, 1982). That's why previous studies suggest organizational conflict as an effective solution to the groupthink phenomenon (Janis, 1972; Ellis et al., 2003; Fernandez, 2005; Solomon, 2006, Janis, 1982; Solomon, 2006). Furthermore, it has been revealed that productive conflict can promote (Solomon, 2006; Sunstein, 2005; Surowiecki, 2004) and reinforce collective intelligence (Page, 2007; A. W. Woolley et al., 2010). In early the days of organizational conflict study, the main line of argumentation emphasized the negative effects (Brett, 1990; De Dreu & Weingart, 2003; K.A. Jehn & Bendersky, 2003).

Considering the possibility of a positive effect became part of the discussion later (Cronin

& Weingart, 2007). These studies pointed out that the context of conflict is more important than the conflict itself. They divided organizational conflict into relational conflict and task conflict to explain the different effects. Task conflict can provide positive effects on organizational performance (Kanter, 1988). Since task conflict can provide the chance to reconsider contradictory alternatives, share new information (De Dreu, 2008; De Dreu & Van de Vliert, 1997; Xie & John, 1995), and task conflict can have a positive effect on organizational performance (Kanter, 1988). Conversely, relational conflict induced by individual preference, favor, and value can raise emotional discords which aggravate organizational or individual capabilities (A. C. Amason, 1997; Simons & Peterson., 2000). in most cases, relational conflicts are known to have a detrimental effect on organizational performance. In this study, the conceptual boundary is limited to task conflict.

2.4.2 Reconsideration of alternatives

The second factor is “reconsidering decision making.” This factor provides a chance to reconsider existing solutions or creating new potential solutions known as alternatives. Additional discussion about alternatives is perceived as an effective solution to attenuate the groupthink phenomenon (Chapman, 2006; I. L. Janis, 1982; Longley, J., & Pruitt, 1980; Park, 2000). Park (2000) pointed out that a lack of alternatives makes groupthink the source of organizational failure. To make alternative knowledge, Turner & Pratkanis (1998a) suggest three techniques involving structured discussion, protecting minority, and reconsidering decisions. The reconsideration of alternatives is not only for the purpose of finding successful alternatives. If the reconsideration about defective alternatives is inhibited, the organization becomes more aversive (Esser, 1998).

In terms of collective intelligence, reconsideration is an effective system to generate better solutions because it can extend the information pool of an organization (Miranda & Saunders, 1995). Filtering of knowledge is also a critical issue in the collective intelligence system. Reconsidering alternatives can provide quality knowledge to the organization through the repeated verification and sharing of results among people (Reia et al., 2019). Another positive aspect is that reconsideration can improve individual capabilities. Accumulated reconsiderations of alternatives improves the individual cognitive boundary which is called background knowledge (Massari et al., 2019) and abundant background knowledge contributes to organizational flexibility, creativity (Hällgren, 2010), and constructive discussion (Ellis et al., 2003). Clearly, the extension of the individual knowledge domain can attenuate the groupthink phenomenon (Baron, 2005; Flippen, 1999). In this study, reconsideration is described as a tendency to keep existing knowledge and interact with more agents.

2.4.3 Organizational memory

The last factor is organizational memory, including both storing and the reuse process. The definition of organizational memory is the way organizations store knowledge for future use (Cyert, R. M., & March, 1963; Levitt & March, 1988; Stein & Zwass, 1995). In previous studies, grasping prior knowledge has been considered a crucial issue of collective intelligence (Denning, Horning, Parnas, & Weinstein, 2005) because the crowd can make a good decision only if accumulated knowledge exists in their domain (Surowiecki, 2004). In a decentralized organization without any integrated systems, individual knowledge is stored by each member (Atlee, 2003; J. H. Lee & Chang, 2010). Despite it not costing much, over time, the location and content of knowledge becomes unclear or even totally discarded within the organization. This loss of knowledge content can disrupt the cooperation of heterogeneous members (Faraj, Jarvenpaa, & Majchrzak, 2011; Kane, Majchrzak, Johnson, & Chenisern, 2009). Consequently, the lack of organizational memory is able to block essential channels for generating new organizational knowledge (Maciuliene & Skarzauskiene, 2016).

In the organizational view, organizational memory performs two roles (Moorman & Miner, 1997). First, it functions as interpreter by filtering the knowledge (Cohen & Levinthal, 1990; Day, 1994; Sinkula, 1994; Walsh & Ungson, 1991). Second, it creates a guideline by influencing on the behavior of organization (Cyert & March, 1963; J. G. March & Simon, 1958; Moorman & Miner, 1997). Organizational memory also takes an important role in the organizational learning process (Huber, 1991). An output is the consequence of organizational memory and its learning process, and consequently, the performance and outcomes of the organization can be determined by the organizational memory and learning (Antunes & Pinheiro, 2019).

In summary, organizational memory not only supports the performance of collective intelligence but also enhances organizational performance and outcomes. That is why it is rational to consider the switching factor of groupthink. This study defines the organizational memory as a process including acquisition, storing, and retrieval (Stein & Zwass, 1995).

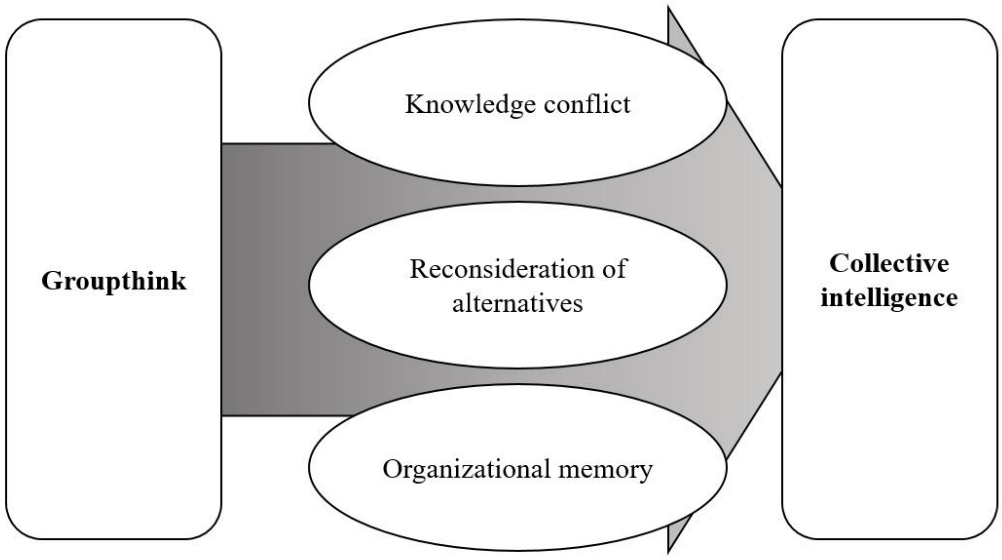


Figure 7. Role of switching factors

2.5 Technology and organizational knowledge

Technology is a critical factor and basis of knowledge creation and management. The advances in ICT facilitate cooperation of organization even though they are geographically dispersed. ICT-based knowledge management system make people going beyond the socio-cultural obstacles which inhibit knowledge interactions, such as politics, trust, authority, hierarchy or concerns about personal relationships (Omotayo, 2015; Sun & Scott, 2005).

2.5.1 Big data analytics

Knowledge is created by many ways, and big data analytics (henceforth BDA) technology is one of them. BDA has been spotlighted as a powerful method to excavate hidden knowledge that human cannot recognize. In other word, BDA system doesn't request any proposed answers for knowledge creation (Kvasnička & Pospíchal, 2015). Recently, BDA technology has achieved a lot of progress in many ways through the aritificial intelligence algorithms such as deep learning and machine learning. So, people are expecting the artificial intelligence to deal with the intellectual problem which is too complex for human to solve. Obviously, BDA technology is an effective way to support human decision makings and knowledge creation (Malone & Bernstein, 2015) in two ways. First, BDA technology is effective in classifying something (De Vincenzo et al., 2018). Second, the coexistence of characterization and diversification is one of the major strength of BDA(Täuscher, 2017; Weld, Adar, Chilton, Hoffmann, & Horvitz, E., Koch, 2012). Thanks to the novel properties of BDA, it is likely to affect to the organizational efficiency, effectiveness, competitiveness and creativity (Kohn & Hüsig, 2006). In addition, from the knowledge management view, the field of BDA can help sharing, transforming individual knowledge, and reincarnating organizations into knowledge organization (Liebowitz, 2001).

Despite the benefit of BDA, intoduction of BDA may not be a better solution if some conditions are not satisfied. From a conservative perspective, it was argued that some prerequisite is necessary to effectively use artificial intelligence technology. It means that BDA does not always bring positive effects in every cases. The excessive use can reduce human cognitive scope and routinize knowledge process, and finally it can make us moving away from creating new knowledge. Kornienko et al. (2015) proposed several factors making necessary to use the advantages of BDA (see Table 8). Also, BDA cannot be utilized in dealing with the abstract concepts such as insight, vision or culture (Mcafee & Brynjolfsson, 2012). Fundamentally, the reliability of BDA should be examined by a human because the resource of BDA can be inconsistent and inadequate (Janssen, van der Voort, & Wahyudi, 2017; Kadadi, Agrawal, Nyamful, & Atiq, 2014). To sum up, BDA is an effective method for supporting the knowledge creation process while human interventions are engaged ate a certain level.

Table 7. The methods to use advantages of BDA systems

Subject	**Method**
Concreteness	Specification of knowledge used in systems
Retrieval	Knowledge search and representation
Expression	Ways of representing the knowledge and their specific feature
Knowledge engineering	Visualization and formalizing conceptual knowledge
Maintenance	Specificity of knowledge representation and gnoseological potential
Inheritance	Transmitting knowledge to other systems

2.5.1 **Online platforms**

Information and communication technology has changed the knowledge process of organizations which producing new knowledge. Especially, online platforms begin to contribute significantly to knowledge collaboration including knowledge producing, sharing, modifying and storing (Faraj et al., 2011). Online platforms can reinforce the common interest to achieve collective welfare (Sproull & Arriaga., 2007), and help to emerge collective intelligence (Luo, Xia, Yoshida, & Wang, 2009). Especially, people using online platforms is likely to lead to better knowledge than off-line organizations Luo, Xia, Yoshida, & Wang, 2009) by communication and interaction among anonymous users (Y. Lee, KIm, Lee, & Kim, 2002). In addition, anonymity and hidden social characteristics provide an unbiased interaction to users. These properties are able to give a positive influence on achieving each user's goal through effective and equal participation (Walther, 1992)(Walther, 1992). For those reasons, previous studies argued that the online platform can encourage knowledge collaboration using social bonding in the virtual space (Tidwell & Walther, 2002; Walther, 1992).

According to Singh and Gupta (2009), online platforms are able to be classified into two broad forms. The first form, collective knowledge system, simply collects users' knowledge and visualize them (e.g., Wikipedia, Youtube, Myspace, and etc.). So, the major goal of collective knowledge system is to reorganizing and filtering the dispersed knowledge. The second form is a system which more properly leads to collective intelligence. This system refers to the web application, like tagging, evaluating, recommending systems, which integrate and recombine individual knowledge from users. Thus the web application puts more weight on knowledge creation than the knowledge collective system.

Then, why do users want to participate in the online platform? To increase the participation of users in the knowledge creation process, previous literature has discussed the motivations for participating in online platforms. According to them, the knowledge creation and collaboration in online platforms are promoted by internal and external incentives (Bock, G. W., & Kim, 2002).

The external incentive refers to the reward that directly satisfies one's desire, such as monetary reward, learning opportunity, and career (H. Hall, 2011). Grosso (2001) argued that ‘so-called need’ is satisfied when individual uses online platforms, and Bishop (2002) suggested that the online platform provide deficit needs to people and this can meet ‘being need’ which is higher desire than the deficit need.

On the other side, the internal incentive can encourage the sharing and producing knowledge in the online space. The internal incentive is an indirect incentive, like reputation, satisfaction, and esteem. In addition, strong trust toward the knowledge they have can improve the knowledge sharing of online space (Jarvenpaa, S. L., & Staples, 2001). Also, Bishop (2007) argued that satisfying ‘social and esteem needs’ is a major factor of online platform participation.

In the collective intelligence studies, online platforms are one of the core systems encouraging cooperative interaction or competition. Online space is very good example of collective intelligence because it has two differences distinguish them from the off-line organizations. These differences are also closely related to the condition of occurrence of collective intelligence.

First, the online platform prevents the monopoly of knowledge. The organization that small group occupies most of organizational knowledge is a centralized organization. The main problem of this organization type is to inhibit the intervention of diverse perspectives. Consequently, the centralized organization raise the authority of expert group, and most of the members may be alienated from knowledge production process. So, previous studies have continuously highlighted the importance of information and communication technologies. Choi (2009) argued that the network can bring a horizontal structure, and its connectivity integrates the fragmented knowledge into collective intelligence. Similarly, Woolley et al. (2010) and Engel et al. (2014) found out that the equal communication determines the level of collective intelligence.

Second, the properties of online platform guarantees high level of diversity (Spielman, 2014b). Diversity of organization is an essential factor inducing collective intelligence (Loasby, 2002) because it prevents polarization (Faraj et al., 2011) and enhances adaptability (Macal & North, 2005). Woolley et al. (2015) found out that the cognitive diversity of people is closely related to collective intelligence when the organization requires creativity and innovation. However, every type of diversity is not effective in collective intelligence (Joshi & Roh, 2009). The level of diversity and quality also can be matters. For example, Aggarwal & Woolley (2013) captured that too high level of diversity decreases the level of collective intelligence. Nonaka (2008) also emphasized the relevance of diversity to a task to be solved.

Third, the online platform enable people interact freely. If diverse ideas are just scattered on uncertain locations, collective intelligence cannot occur. That’s why knowledge interaction is essence of collective intelligence (Massari et al., 2019). The online platform radically improves the connectivity which is an important factor to understand knowledge interaction (Solé et al., 2016), and knowledge interaction advances organizational knowledge to higher stage which is more complex and abstract (Hwang, Choi, & Kim, 2009). Dutton (2008) suggested three types of collective intelligence, and argued that interactions of knowledge and information should be requested to create new knowledge. Furthermore, the interaction in online space can give significant influence on the individual knowledge and behavior (Hartmann, 2010).

In this dissertation, the use of online platform and collective intelligence are assumed to have an inverted-u shape. Solomon (2006) and Erdem (2003) argued that too frequent communication decreases collective intelligence and also makes an organization too risk-aversive. Especially, diversity in the online space aggravate the performance of an organization requiring high efficiency (Woolley et al., 2015). In addition, Axelrod (1997) argued that frequent and continuous interactions may reduce the residual heterogeneity of an organization, and also Courtright (1978) figured out that an organization with frequent valid interactions is likely to suppress any heterogeneous ideas.

Chapter 3. Is groupthink really inevitable?: based on self-organization aspect

3.1 Introduction

At the early stage of knowledge creation studies, the role of experts had got more attention

(Gruber, 1989). As the problems and their solutions gradually had become huge and complex, knowledge creation get more difficult to be taken by the small number of experts and individuals. Nowadays, the value of organizational knowledge has been increased unprecedentedly in most social organizations such as industry, public sector, and our daily lives (Liebowitz 2001; Grant, 1996; Nonaka, 2000). So, organizations have attempted to acquire both width and depth of knowledge through competition and cooperation of organization (Bock & Kim, 2002). However, there is an old obstacle for organizational decision making area called ‘groupthink’.

Groupthink is defined as a mode of thinking that group members engage in when they are dominated by the concurrence-seeking tendency when their strivings for unanimity override their motivation to appraise the consequence of their action (Janis, 1982). Groupthink was a restriction of decision making and strong motivation for unanimity during the organizational knowledge creation process (Hart, 1991). Empricial evidence supported that this tendency of concurrence-seeking may lead to a premature consensus and finally, brings the detrimental organizational outcomes (Callaway et al., 1985; Courtright, 1978; Flowers, 1977; Fodor and Smith, 1982; Leana, 1985; Montanari, 1986). Janis (1982) explained this phenomenon through a model consisting of several factors: antecedents, symptoms of groupthink, symptoms of defective decision making and quality of outcome. Janis’ groupthink model is intuitive and simple to understand groupthink phenomenon, so many studies had adopted this model during about 20 years (Esser, 1998; Truner & Pratkanis, 1998; Riccobono et al., 2016). Despite some differences in context, concept or measurement, groupthink studies have agreed with an argument that groupthink brings the failure of group decision-making was based on Janis' linear causalities (Rajakumar, 2019; Riccobono, Bruccoleri, & Größler, 2016). Thus, previous studies have tried to prove that the quality of outcome can be improved by inhibiting the antecedents of groupthink.

Despite the pervasive use of Janis' model (e.g. Esser and Lindoerfer, 1989; Manz and Henry P. Sims, 1982; Park, 1990; Peterson et al., 1998; Raven, 1998), this framework led to some criticisms. First, the definitions and measurement of Janis groupthink model was ambiguous (Turner & Pratkanis, 1998c; Longley & Pruitt, 1980). Also, the factors of groupthink model were difficult to observe from the outside of organization (Park, 1990). That is why there have been no sufficient studies to support Janis' model empirically. Furthermore, the results of studies to re-test Janis' groupthink model have conflicted with the key assumption of Janis' model (e.g., Flowers, 1977; Fodor and Smith, 1982; Hart, 1991; Miranda and Saunders, 1995; Park, 2000). On the different perspective, the linear and static framework of Janis' model have been criticized. Hart (1991) argued that the groupthink phenomenon can be one of the results produced by interactive behaviors among group members. After that, Janis(1982) adopted the possbility of other reason for groupthink. About that, Aldag and Fuller (1998) explained the resaon why groutphink model is inconsistent. Consequently, despite its importance, dynamic perspective of organization has been considered as a trivial side of groupthink phenomenon (Whyte, 1998).

To provide solutions for those criticisms, three kinds of streams occurred (Turner and

Pratkanis 1998a). The first group, that most of groupthink studies belong, suggested some modifications of Janis model with maintaining the overall framework (e.g., Chapman 2006; Erdem 2003; Flowers 1977; Manz and Henry P. Sims 1982; McCauley 1989; Packer 2009; Turner and Pratkanis 1998b) and the second group focused on practical usage of groupthink model rather than validate or test Janis' model (e.g., Bénabou, 2013; Hällgren, 2010; Paul't Hart, 1991; Manz & Henry P. Sims, 1982; Pidgeon & O'Leary, 2000). The last group of those streams have argued an alternative approach especially based on dynamic perspective of groupthink (e.g., Mok and Morris 2010; Solomon 2006; Tao 2018). This stream of the study emphasized a totally different model, for example, swarm intelligence, collective intelligence. In addition, the dynamic perspective suggested that specific contexts can stimulate the occurrence of the groupthink phenomenon (Turner, Pratkanis, Probasco, & Leve, 1992).

Of course, there have been a few improvements to find out why groupthink phenomenon occurs through these studies. However, not only empirical evidence of groupthink is still insufficient and contradictory but also considering the dynamic perspectives of human organization is very rare (Rajakumar, 2019).

So, this study aims to identify an alternative way to manage groupthink phenomenon if groupthink phenomenon is inevitability. In other words, when groupthink is necessary phase of organizational decision making process, eliminating groupthink from the organization may suspend that process. To provide more effective point of view for groupthink phenomenon, this study focused on finding the differences between traditional framework of Janis (1982) and dynamic view based on bottom-up process. This study compared the results to identify two research questions: ‘what is the mechanism of groupthink emergece?’ and ‘which factor will affect the qualtiy of organizational outcome?’. So this study assumed that groupthink can be a result of dynamic process rather than static and linear causalities. Under this assumption, this study tries to answer to thoes questions by comparing the tradntional groutphink model and dynamic ones involving self-organization perspective. Thus, this study adopted two models, one is based on Janis (1982) and another is a complex adaptive system based on self-organization (Massari et al., 2019).

This study used two methodologies to present the difference and conflict between conventional and dynamic perspective of groupthink. First, structural equation model analysis, which is based on ANOVA, was adopted to show the validity of not only individual relationships but also holistic causalities. This study conducted a survey for 300 Korean people, and used this survey data for testing the structural equation model. In the second analysis, agent-based model simulation was conducted, because this method is good for understanding a complex adaptive system such as self-organization (Smith & Stevens, 2017).

This study articulated groupthink phenomenon through the ABMS. From those two analysis, this study can show the differences between two perspectives clearly. At first, antecedents of groupthink are the significant determinants of groupthink phenomenon, but they are not directly connected to the quality of organizational outcome. In other word, groupthink phenomenon itself can be emerged by antecedents of Janis (1982), it is unsure that groupthink can deteriorate the quality of organizational outcome. The second analysis using the ABMS present a different consequence with previous groupthink studies. There are two major findings, first one is that groupthink phenomenon can be emerged by only individual interactions without any antecedents of groupthink. Another finding refers to that the antecedents of groupthink may deteriorate the quality of organizational performance rather than groupthink phenomenon itself.

From those results, we can conclude that groupthink is not a phenomenon coming from the linear causalities but caused by the collaboration of individuals. Our conclusion is opposite to the existing studies taking a stance of Janis' groupthink framework. In addition, the results imply that antecedents of groupthink are more related with the quality of outcome. In other words, antecedents of groupthink only affect to the quality of outcome, and groupthink is a natural phenomenon of organization.

Based on this study, we can suggest different strategies to manage the organizational decision making process. All results of this study support that groupthink phenomenon is a natural reponse of organizational interaction. So, if an organization want to improve their quality of outcome, groupthink is not a matter. Rather, the group cohesiveness and structural faults known as the antecedents of groupthink, should be more rigidly limited.

The outline of the remainder of this study is as follows: Section 3.2 delivers the literature review about groupthink and its criticisms. Section 3.3 presents the description of re-testing model of Janis' groupthink model through SEM analysis and the ABM analysis for groupthink phenomenon based on self-organization aspect. Also, the results of each analysis are provided in this section. Section 3.4 concludes the study with discussion of results in terms of research questions.

3.2 Revisiting Janis' groupthink model

3.2.1 Evidence of Janis' groupthink model

In this study, we performed a SEM analysis to examine the validity of causalities in Janis' model. Although there were a lot of studies on Janis' groupthink model, most of studies had focused on laboratory experiment and case studies (Riccobono et al., 2016; Turner & Pratkanis, 1998c). Previous studies pointed out that the antecedents of groupthink are hard to observe from the outside of organization (Turner & Pratkanis, 1998a), so experiments or survey is necessary to collect the dataset. However, since groupthink theories were rooted on the experimental psychology area (Janis, 1972), role play based experiments have been more prefered in the previous studies (M. R. Callaway & Esser, 1984; Courtright, 1978; Flowers, 1977; Park, 2000; Turner et al., 1992). However, the laboratory experiment has some limitations in terms of generalization because it is very dependent on the capability of experiment designer. Lee et al. (2016) used a SEM analysis to show the validity of Janis' groupthink model. However, since Lee et al.(2016) captured the individual causalities of Janis model, it did not present the unified effect of antecedents and sysptoms of groutphink. Thus, this study adopted a SEM methodology to compensate the result of social experiment method based studies.

Also, SEM has advantages under the certain condition. Although the SEM method itself can not capture the casualities, it is possible if there is a theoretical support. Basically, SEM is a certain form of the confirmatory factor anlaysis (Cha, Hwang, & Lee, 2019). In other words, since the theory-based hypothesis is an essential part of CFA, it is hard to identify the causalities among unstructured variables. However, it is an effective method for verifying relationships created by a theoretical basis (Kline, 2015). In addition, since SEM is a holistic method that estimates multiple relationships simultaneously, it is effective in minimizing the accumulation of errors from sequential estimates (Cha et al., 2019). This methodological strength helps SEM become an effective means of testing the hypothesis in Janis' groupthink model. This study used *Lavaan* package in R to estimate the SEM.

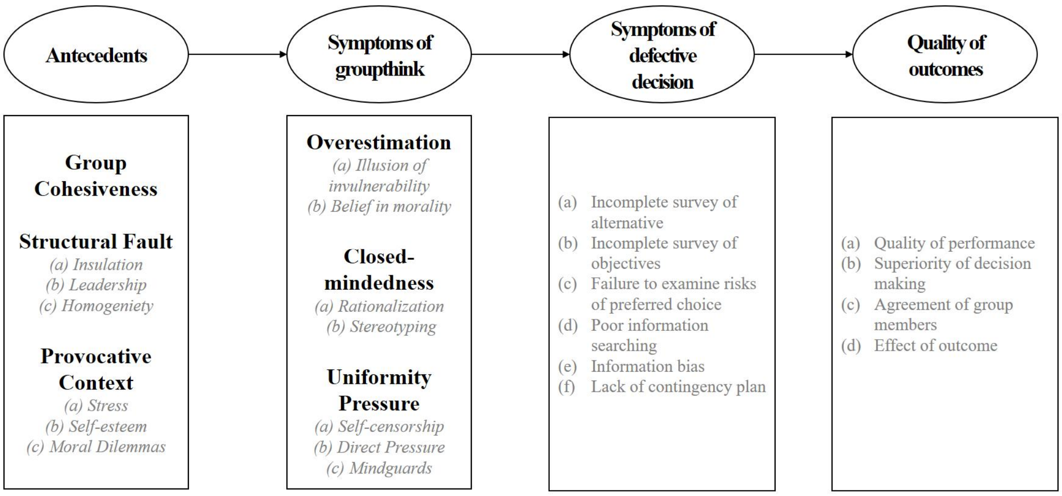


Figure 8. Janis groupthink model and its components

3.2.2 **Data**

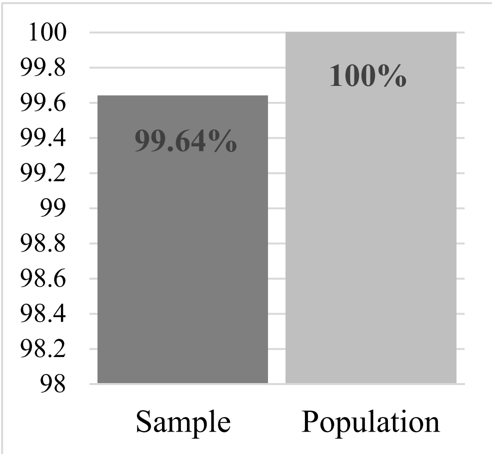
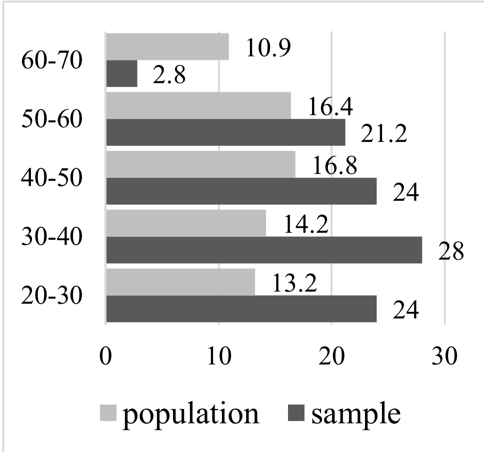
This study conducted a survey on 300 respondents who belong to an organization which create intellectual outcomes such as patent, technology, product or services. In the pre-stage of the survey, respondents who do not participate in organizational behaviors were excluded. Middle and high school students were excluded and self-employees also were out of consideration because they are not likely to collaborate with others to create organizational knowledge or decision. The main survey was conducted toward the Korean people during 5 days in June of 2017. The survey was conducted on the online platform provided by Membrain, which is the survey specialized firm in Korea.

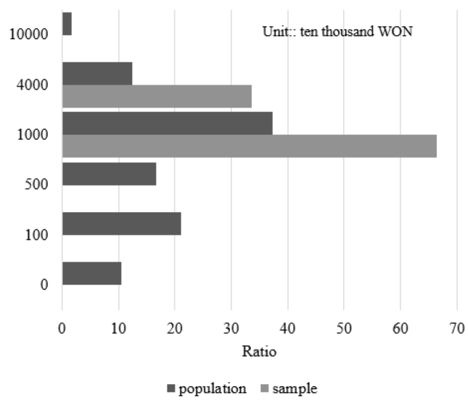
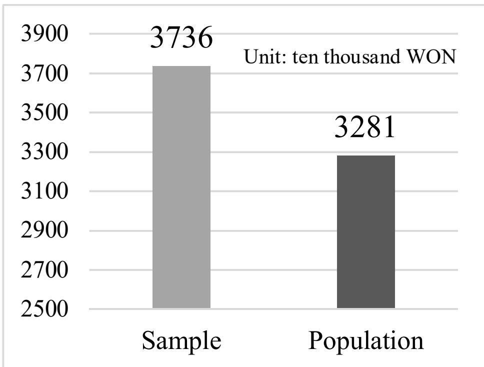
The questionnaire of this survey consist of 24 items. Each items explain the components of Janis' groupthink model. Each antecedent, which are cohesiveness, structural faults and provocative context, involves 8 items. The symptoms of groupthink consists of 6 items and the symptoms of defective decision includes 7 items. Lastly, the quality of outcome has three items. The details of each item will explained the following section.

Finally, this study collected 300 responses from people who participated in a knowledge process. We eliminated 49 respondents who either did not answer in full or who showed an extremely biased response pattern. Finally, we tested the validity and consistency of Janis' model through confirmatory factor analysis (CFA) based on the sample data for 251 respondents that we finally obtained.

Since the sample should reflect the population of research subject, this study compared the demographic characteristics between the sample data and actual population of Korea in table 9. Furthermore, the respondenst's characteristics were presented by 5 aspects related to their organizations. The 80% of respondents belong to the private firms and 11.6% belongs to the R&D institute. The 60% of respondents is in admistration and financial division, 24% is in the distribution division, 5.6% is in R&D division and 4.4% is in marketing. Also, in terms of their position, 69.6% of respondents is full-time employee, 16.4% is part-time employee or free-lancers, 9.6% responsdents are managers, and only 0.24% of respondents is the board member. In addition, more than half of respondents have less working year than 4 years (55.6%), and the average working-year is 5.8 years. The average size of oranization 263.8 and the standard deviation is 2,450 because of the outliers which have more than 10,000 members.

Table 8. Sample statistics and population.

Gender ratio	Age
	
(Source: Statistics Korea, 2018)	(Source: Ministry of Public Administration and Security, 2018, Total Survey of Population and Housing in 2018)

Income	Average income
	
(Source: N. Kim, 2015)	(Source: Statistics Korea, 2018)

3.2.3 **Measurement**

The detail questions for each factor are shown in the appendix 1. All questions for the survey, except for the items relevant to demographics, were measured using a 5-point Likert scale.

To show the validity of items, internal validity should be tested before SEM analysis. Cronbach alpha present the internal consistency which means that the items are well organized and structurized. Generally, Cronbach alpha can have a value from 1 to minus infinity. Cronbach alpha is calculated as shown below. Also, R-square is well-known index to represent the explanatory power of model. In the SEM, R-square value reports the fraction of variance explained by each items.

$$Cronbach\ \ alpha = \left[\frac{Number\ \ of\ \ items}{Number\ \ of\ \ items - 1}\right] \times \left\{1 - \left[\frac{\sum_{i=1}^{\#\ of\ \ items} Var(x_i)}{Var(\sum_{i=1}^{\#\ of\ \ items} x_i}\right\}$$

We calculated the Cronbach alpha and R-square values to identify the internal consistency of our questionnaire and found that most items were within the recommendations provided in the previous literature (Fornell & Larcker, 2014; Hair, Black, Babin, & Anderson, 2006; Kim & Ha, 2011). The basic statistical description of each item is in appendex 2.

Table 9. Summary of questionnaire statistics

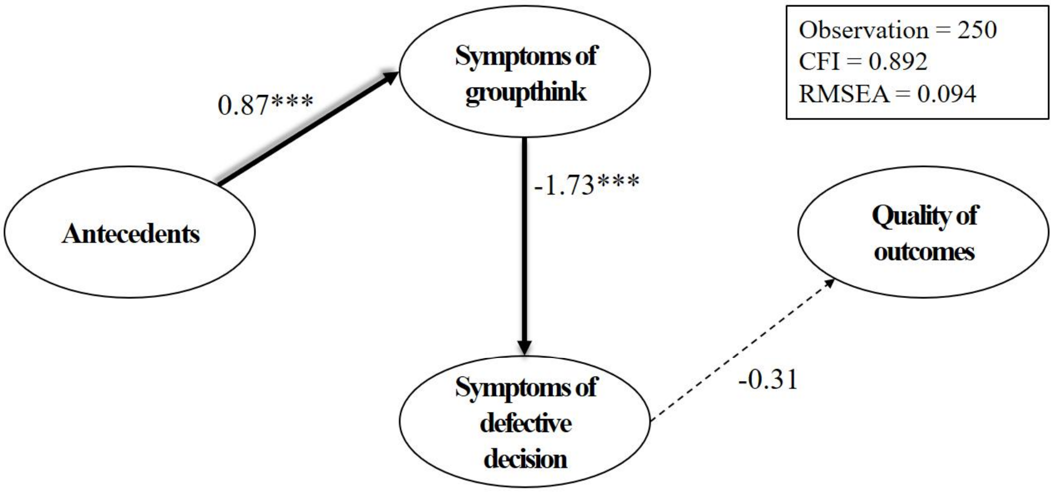
Item	No	Reference	Cronbach alpha	R-square
Group cohesiveness	GC01	Leana(1985)	0.79	0.934
	GC02	Leana(1985)		0.451
Structural fault	SF01	Janis(1972), McCauley(1998)	0.64	0.778
	SF02	Janis(1972), McCauley(1998)		0.386
	SF04	Janis(1972), McCauley(1998)		0.141
Provocative context	PC01	Janis(1972), McCauley(1998)	0.77	0.503
	PC02	Janis(1972), McCauley(1998)		0.463
	PC03	Robinson and Shaver(1973)		0.631
Overestimation	OE01	Chapman (2006), Hart(1991)	0.91	0.537
	OE02	Chapman (2006), Hart(1991)		0.646
Closed-mindedness	CM01	Janis(1972), Ferraris and Varveth (2003)	0.72	0.603
	CM02	Janis(1972) , Ferraris and Varveth (2003)		0.519
Uniformity pressure	UP01	Janis(1972), Hassan and Golkar (2013)	0.61	0.609
	UP02	Janis(1972), Hassan and Golkar (2013)		0.376
Symptoms of defective decision-making process	SD01	Janis(1982), Moorhead and Montanari(1986)	0.84	0.720
	SD02	Janis(1982), Moorhead and Montanari(1986)		0.756
	SD03	Janis(1982), Moorhead and Montanari(1986)		0.555
	SD04	Janis(1982), Moorhead and Montanari(1986)		0.603
	SD05	Janis(1982), Moorhead and Montanari(1986)		0.508
	SD06	Janis(1982), Moorhead and Montanari(1986)		0.647
	SD07	Janis(1982), Moorhead and Montanari(1986)		0.154
Quality of outcome	QO01	Riccobono et al (2016)	0.78	0.621
	QO02	Kariv and Silverman (2013)		0.447
	QO03	Hollen (1994)		0.573

3.2.4 Retesting Janis groupthink model

Our study carried out a SEM analysis of the questionnaire data to retest Janis' groupthink model. Our model set the relationships among the variables based on the linear model presented by Janis (1972). The results of the SEM analysis showed that Janis' groupthink model was partially supported as suggested in previous studies. The positive relationship between the antecedents and symptoms of groupthink corresponded to Janis' model. However, contrary to the original model, our analysis shows that the symptoms of groupthink decrease the symptoms of defective decision-making, and that there is no significant connection between the symptoms of defective decision-making and quality of outcomes. Much like Janis' model, the antecedents are likely to affect the groupthink phenomenon. However, Janis' hypothesis that groupthink exacerbated the quality of outcome produced by the organization may be contradictory.

There has been a controversy over the assumption that groupthink decreases organizational performance. According to previous studies, although the groupthink phenomenon may aggravate group decisions (Janis, 1972,1982; Longley, J., & Pruitt, 1980), the quality of alternatives considered during the organizational decision-making process is likely to be a more dominant factor in determining organizational performance (Paul't Hart, 1991; Neck & Moorhead., 1995). The SEM result provides a perspective that is similar to that provided in previous studies to the effect that the relationship between groupthink and organizational performance varies on account of several conditions such as individual traits (Manz & Henry P. Sims, 1982; Riccobono et al., 2016) or psychological factors (Bénabou, 2013;

Packer, 2009). We established an agent-based model simulation (ABMS) to capture both triggers stimulating the negative effect of groupthink and the role of antecedents in the concurrence-seeking process.



Path	Coeff.	Janis(1972)
Antecedents → Symptoms of groupthink	0.87**	+
Symptoms of groupthink → Symptoms of defective decision making	- 1.73**	+
Symptoms of defective decision making → Quality of outcomes	- 0.31	-

Figure 9. The result of SEM analysis

3.3 Groupthink simulation model

Studies on collective intelligence adopted the complex adaptive system because of the high complexity as a result of involving a number of interactions (Schut, 2010). However, the understanding of groupthink depended on several linear causalities based on Janis' groupthink model (J. Esser, 1998; W. Park, 1990). Furthermore, the dynamic aspect manifesting in forms such as interactions (Riccobono et al., 2016), network (Packer, 2009), and trust (Erdem, 2003) had been neglected.

The present study proposes an ABMS emphasizing self-organization aspect. ABMS based on self-organization theory has received the attention of social science researches (T. S. Smith & Stevens, 2017), because it can describe ‘bottom-up’ mechanism (Casti, 1994; Seidenberg, 1993) which means that the social phenomenon occurs by interactions among people (Simmel, 1971). Thus, we constructed agent based model under the assumption that the groupthink is a self-organized phenomenon. Basically, ABMS of the present study follows the model of previous complex adaptive system studies. Since the emergence is a non-linear phenomenon, our simulation model was characterized by the dynamic environment and mediators which is the way of interpreting the information of the environment (T. S. Smith & Stevens, 2017). The environment of groupthink includes agent’s way of interaction, network structure, group size, and the objective function, and the mediator refers to the personalized properties such as sociality, learning capability, efficacy and etc. In this context, the part that multiple variables affect to the specific aspect seems like a characteristic of the multivariate mode, but the complexity of the components and its linear indivisibility are the unique properties of the complex adaptive system (Simon, 1996).

In the previous study such as Reia et al. (2019), the concept of complex adaptability was introduced into cooperative problem solving process. Although Reia et al. (2019) focused on the influence of the way how to share intra-organizational information, groupthink was considered as just one case of failed cooperation. Different to that, our ABMS mainly dealt with groupthink and its effect on the organizational performance to verify Janis' groupthink model. This study developed the ABM simulation based on Python 3.5.

Despite the great potential of the ABM, it comes at cost. Basically, ABMs are more complex than the other analytical models in terms of structure, so ABMs necessarily require the power of computer (V. Grimm, 1999). Because of the gap between the computer and human language, the results obtained from an ABM are not easily reproduced (Hales, Rouchier, & Edmonds, 2003). To solve this problem, this study adopted ODD protocol which stands for three components 'Overview', 'Design concepts' and 'Details' (Volker Grimm et al., 2006).

Table 10. Seven element of ODD protocol

Overview	Purpose
	State variables and scales
	Process overview and scheduling
Design concept	Design concepts
Details	Initialization
	Input
	Sub-models

(Source: Grimm et al., 2006)

3.3.1 Overview

3.3.1.1 Purpose

This study constructed an agent-based model under the assumption that groupthink is a self-organized phenomenon. ABMS, based on the self-organization theory, has been engaged with in social science studies (T. S. Smith & Stevens, 2017) because it can describe the "bottom-up" mechanism (Casti, 1994; Seidenberg, 1993) of social phenomena caused by interactions among people (Simmel, 1971). Especially, this is not the first groupthink study to use ABMS. Reia et al. (2019) adopted an ABMS to understand how to share information and knowledge in an organization and the impacts of doing so. On the other hand, this ABM mainly deals with groupthink and its effects on organizational performance to verify Janis' model. The models will be examine in the two aspect, which are the organizational performance and the diversity.

3.3.1.2 State variables and scales

The use of ABMS in this study follows the models used in previous studies on the complex adaptive system. This ABMS consists of the environment and the medium (Smith & Stevens, 2017). Both leayers are linearly indivisible, which is a unique property of the complex adaptive system (Simon, 1996). Environment layer refers to the organization, and the medium layer refers to individual person in the organization. The environment for groupthink includes the agent's mode of interaction, the network structure, the group size, and the objective function. The medium refers to more personalized factors such as sociality, learning capability, and efficacy, etc (Smith & Stevens, 2017).

(1) Medium layer

Medium is a unique characteristic of an agent determining how to interpret and evaluate given information and knowledge. Complex adaptive systems consist of independent and heterogeneous entities that can interact with their environment (Beinhocker, 1997; Gell-Mann, 1994). Thus, manipulating the relationship between input and output through the properties of a medium (M. J. North & Macal, 2007) is an effective mea of describing the characteristics of a system (Beinhocker, 1997; Choi, Dooley, & Rungtusanatham, 2001;

Stacey, 2000). Contrary to the system dynamics, the medium in complex adaptive system is heterogeneous and independent. In other words, in the dynamic system, there is one medium per system, but this is not so in the complex adaptive system. This is why self-organization takes place in complex adaptive system (Anderson, 1999).

Members of the social organization that are called “agents” in ABMS, generally have a typical set of behaviors. “Learning capability” is one of the common behaviors that members of social organizations engage in repeatedly. At the organizational level, “learning capability” refers to the exploitation of existing resources (March, 1991) for the construction of background knowledge (Levitt & March, 1988). The present study assumed learning capability (μ_i) as the probability of imitating another agent’s knowledge.

In the medium layer, the agents are homogeneous in terms of demographic properties, such as gender, age, location, education level. So, the agents can be distinguished by other parameters randomly allocated at the initial stage of simultion. The parameters are learning capability, collaboration ratio and creativity. Learning capability and creativity have the same theoretical foundation which is evolutionary computation. March (1991) introduced a framework of evolutionary computation in the organization dynamics, through some assumptions that the imitation of evolutionary computation refers to the learning capability and the mutation of gene refal amoers to the individual creativity. Also, March’s work presented that the fitness of gene string can be applied for measuring organizational performance.

Intearaction among group members is not only an essential method for creating competitive capability (Bigham, Bernstein, & Adar, 2015) but also operates as synergetic interactions that determine organizational rationality that surpasses the best individual (Curşeu et al., 2013). Previous studies have supported the idea that collaboration has a positive impact on organizational performance (e.g., Fleming et al., 2006; Hansen and Vaagen, 2016; Lee and Bozeman, 2005; Lim and Park, 2010; Maciuliene and Skarzauskiene, 2016). Interactions have especially is a critical capability of organizations because they were found to be affected by collective intelligence rather than individual competence such as IQ or education level (A. W. Woolley et al., 2010). We assumed that intra-organizational collaboration as a recombination process of knowledge functioned by exchanging its own experience with those of other connected agents. The level of collaboration is defined as a frequency of the recombination process (f_{col}) in our ABMS. To sum up, collaboration ratio is a probability to meet another agent to interact their knowledge. This concept is based on the biological interaction defined as a radius of contact between two entities (Prindle & Hasty, 2010). On the aspect of evolutionary computaion model, interaction is defined as a mutual learning process based on learning capability (Posen, Lee, & Yi, 2013). Also, organizational hierarchy affect to the degree and direction of mutual learning process (Halevy, Y. Chou, & D. Galinsky, 2011; Kluger & DeNisi, 1996). The interaction of this research model is as the figure below.

Creativity is a critical ability that is expected from individuals by the organization because it is necessary for the development and maintenance of a competitive advantage (Woodman, Sawyer, & Griffin, 1993). However, there have been various arguments to help figure out a mechanism of human creativity (Kletke, Mackay, Barr, & Jones, 2001). In the complex adaptive system, a mutation has been utilized to explain the accidental creation and evolution of knowledge (Gero & Maher, 2013; Gero, 2006). Mutation can help maintaining the genetic diversity to protect genetic equillibriu, so mutation is a necessary process in the evolutionary computation model (Melchinger, 1999). However, since the mutation has changed individual bit of gene string, mutation is hard to describe in term of the structural dimension. So we also considered not only conventional mutation but also structural mutation. In this model, the probability of mutation (π_i) refers to unexpected changes of element in the agent's knowledge. The structural mutation of knowledge is represented by shifting the average or deviation of one's knowledge set. In sum, personal creativity in our research model depends on two processes: "content mutation" and "structural mutation", and those processes can occur indpedently.

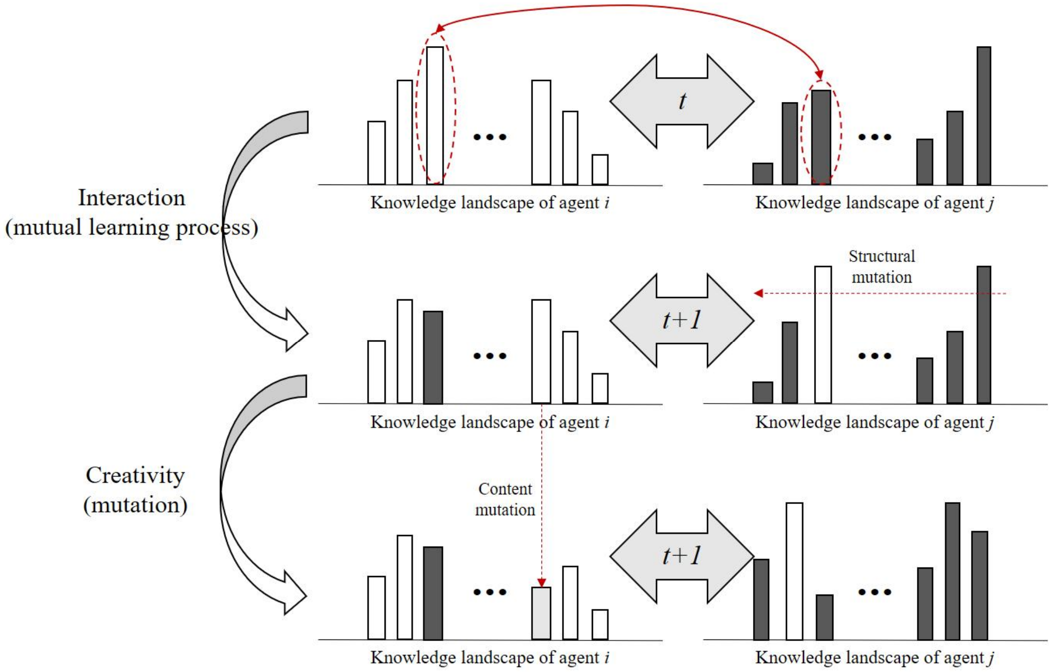


Figure 10. Interaction and creativity of research model

Lastly, similar to that each gene has their unique bits of string, each agent possesses an individual knowledge string. In the previous studies, individual's knowledge string had been represented by binary code (Bäck & Schwefel, 1993; J. March, 1991; Posen et al., 2013), the knowledge string in this study is a little different. This model does not limit the bit of string as a binary code because knowledge is a multi-dimensional concept consisting of other knowledge or information (Nonaka & Toyama, 2003; Nonaka et al., 2006). Also individual knowledge is created by fragmented information, interpretation and combination (McHugh et al., 2016). So, if the organization members share a common knowledge, it can be defective and uncertain because of individual background and context (R. Davis, 1986). Therefore, this study assumes that the knowledge is a form of probability distribution rather than the string of binary code. In this study, distributions of knowledge is called 'knowledge landscape'.

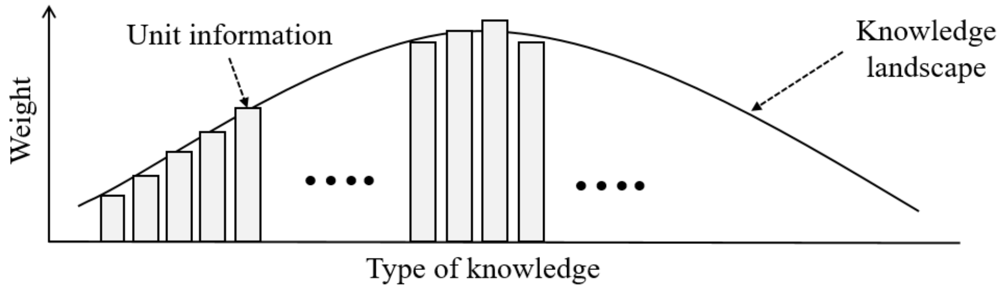


Figure 11. Description of knowledge landscape

(2) Environment layer

The environment layer, which is the higher-level entities, includes integrated information such as population, network, organizational knowledge, or organizational performance and diversity of an organization (Volker Grimm et al., 2006). The environmental aspect of our research model is similar to the organizational structure or systemic elements such as hierarchy, role, procedure, form, network, and norm, etc. (Finifter, 1986). Therefore, the environmental parameters have one value and all the agents share the same value. Sometimes, since the unstructured system such as swarm optimization is based on local interactions, there can be temporary and spontaneous sub-groups. However, a typical social organization has a clear and formalized system (M. J. North & Macal, 2007), so we did not consider the local-optimization or temporary balanced state problem.

The orgnizational performance refers to an alignment with their environment to achieve long term survival and growth (Fiol, Lyles, & Lyles, 1985). In our model, the performance of knowledge was calculated by a similarity between two knowledge landscapes and deviation was derived from a set of unit knowledge. In our ABMS, the criteria of knowledge are represented as a "schema" of an organization. Therefore, the performance of certain knowledge can be calculated based on the gap between "schema" and the current knowledge landscape. This study measure the organizational performance based on Posen et al. (2013)'s generalized form of fitness function (Holland, 1992). Let Y(X) denote the organizational performance with knowledge string X. Formally, Y(X) is suggested as below:

$$Y(X) = f(R, X) = \begin{cases} \frac{1}{m}\sum_{i=1}^{m}(\delta_i \prod_{j=1}^{k} \theta_j^i), \text{if } 1 \le \mathrm{k} \le \mathrm{m} - 1 \\ \frac{1}{m}\sum_{i=1}^{m} \delta_i, \quad if\ k = 0 \end{cases}$$

$$\mathrm{R: schema, m: size\ of\ agent}$$

where $\delta_i = 1$ if the i th element is matches that of the schema, and otherwise $\delta_i = 0$. The only difference with our ABM is that δ_i is binary. In other words, when a certain knowledge mathes to the schema, δ_i is dependent on the difference between i th component. For example, if the organizaitonal knowledge has 0.3 weight an the i th knowledge element and the schema has 0.2 weight, the δ_i is -0.1. So, we uses the squred δ_i to eliminate minus sign, and assume that the ABM process has simple solution space (m=0). Therefore, the measurement of organizational performance is as shown below:

$$Y(X) = \frac{1}{m}\sum_{i=1}^{m} {\delta_i}^2, 0 \le Y(X) \le 1$$

Diversity of an organization is a critical issue in the perfroamnce of evolutionary computation model (Weerayuth & Chaiyaratana, 2002) because proper control of diversity can increase the performance of evolutionary process through the balance between the exploration and exploitation (Chang, Huang, & Ting, 2010), and also bring the stability and robustness of organizations (Macal & North, 2005). The definition of diversity in the simulation studies is a different behavior patterns of agents (Holland, 1992). Measuring the organizational diversity has been conducted in diverse ways, such Hamming distnace, Euclidian distance, Connection matrix or Entorphy model (Chang et al., 2010; Gomez, 2009). In genenral, the hamming distance is for calculating the distance between two gene strings (He, Petoukhov, & Ricci, 2004) when the string has 1 diemsional value such as 0 and 1. However this study assume that the knowledge is a form of distribution, so it is impossible to measure the distance between two knowledge through Hamming distance model. Consequently, based on the fact that probability distributions can be expressed in the form of vectors, this study used the Euclian distance model to measure the distance between the two different knowledge.

Table 11. Measuring diversity of various entities

Hamming distance between vector X and Y: $\mathrm{D(X,Y)}$	Euclidian distance between vector X and Y: $\mathrm{D(X,Y)}$
$I = \sum_{j=0}^{L} I_j, \quad I_j = \begin{cases} 0 & if \;\; x_j = y_j \\ 1 & if \;\; x_j \neq y_j \end{cases}$ $\mathrm{D(X,Y)} = \frac{I}{L}$	$\mathrm{D(X,Y)} = \sqrt{\sum_{i=0}^{N} (x_i - y_i)^2}$
Connection matrix: D(X,Y)	**Information entropy: PD**
$\mathrm{S(X,Y)} = \sum_{i,j} \frac{(x_{ij} \mid x_{ij} = y_{ij} = 1)}{n}$	$H_i = -\sum_{c \in C} pr_{ic} ln(pr_{ic}), where \;\; pr_{ic} = \frac{na_{ic}}{N}$

D(X,Y) = 1 – S(X,Y)	$na_{ic}: number\ of\ appearance\ of\ c\ at\ locus\ i$ $C: number\ of\ cities\ should\ be\ visited$ $PD = \frac{\sum D(X,Y)}{N}$

The simulation model in this study includes the type of network, the level of hierarchy, and decentralization as environmental properties. Network structure of agents can affect on the information diffusion (Barabási & Albert, 1999; Stummer, Kiesling, Günther, & Vetschera, 2015) and organizational performance (Soda & Zaheer, 2012). Also, Dalton et al. (1980) argued that the hierarchical structure of an organization influnce on the organizational performance, and Halevy, Y. Chou, & D. Galinsky (2011) proposed that organizational hierarchy can enhance the performance of organizational outcome and chance of an organization's survival and success too. Although the effect of network structure and hierarchy on the organizational performance is obvious, this study does not engage in the influence of those aspects. Since the purpose of this study is not in the network or its hierarchy, detailed manipulation of these factors will not be conisdered in this study.

The density of network is defined as an average centrality, and the level of hierarchy refers to the relative power of influence among different organizational groups (h_{sup}) designated by the ratio of each group ($r_{sup,k}$). This study assumes three layers that comprise the employee, management, and the decision-maker. The ratio of layers describes the structure of organizational hierarchy and relative influence explains vertical equality. For example, the organization becomes equal and mutually independent when h_{sup} approaches zero, because there is no relative impact. Contrary to that, if h_{sup} is close to one, interactions among the layers depends on the order of ranks in the organization.

How do agents decide their future behavior? To answer to this question, states of agents, that want to maximize their objective function, should be deifned. According to the previous studies on the ABMs, there are two kinds of utility maximization methods. The first method is maximizing the objective function and the another one is minimizing the risk. Also, both two method can coexist in the same model. However, risk or cost of behavior involves a paradox of Famahmand & Spafford (2013), that the increase of risk can be beneficial to the insiders of organization, so maximizing utility is more effective method to develop an ABM for the economic topics (e.g., Arentze, Kowald, & Axhausen, 2013). Based on thses studies, this ABM only conisders the maximizing the objective function rather than minimizing the risk or cost. Each agent in this model has two states. When a new period of simulation begins, the agents in the medium layer should select one state bewtween two states. First state is maintaining the incumbent behavior. In this states, the agents try to maintain the existing behavior when the current individual performance is higher than the previous one. It means that the behavior an agent choose the existing behavior, if the agent perceives the behavior as a successful strategy. However, if the individual performance is decreased, the agent tries to change its knowledge until those changes improve the individual performance. This concept that the agent choose their next behavior for increasing their utility or performance

The agents can modify their own behaviors through knowledge interaction and mutation of individual knowledge. This is the second state, which is the modifying state.

(3) Antecedents of groupthink

Janis (1972) suggested 7 antecedents inducing the groupthink phenomenon in an organization. The 7 precedence factors consist of group cohesiveness, insulation, leadership, lack of norm, and procedure, homogeneity, external pressure and low efficacy. We adopted 5 factors except the provocative context involving external pressure and low efficacy because of two reasons. First, provocative contexts are hard to control to achieve the organizational goal. The main reason is that the sources of external pressure are numerous, so it is impossible to define them as one measurement. Second, it is close to the field of psychological research rather than a social science study. It strongly depends on the invisible elements such as personality or psychological background, observing those factors on the organizational level is impossible. In addition, previous groupthink studies did not consider the provocative context as a source of groupthink as importanlty as group cohesiveness or structural faults (Chapman, 2006). As a result, we designed our ABMS as an isolated system excluding the provocative context of Janis (1972). Finally, we adopted 5 antecedents and presented the following operational definition for each factor.

Group cohesiveness is defined as a strong motivation to reside in an organization based on the positive perception toward the organizational decisions (I. L. Janis, 1982). Previous studies measured the cohesiveness through the assessment toward own group or emotional cognition (Breitsohl et al., 2015; S. T. Lee et al., 2016). In other words, high cohesiveness makes people want to be a member of an organization rather than become an autonomous entity, and it is realized by consensus or compliance with group decision-makings (Turner

& Pratkanis, 1998a). Thus, in this research model, we described the group cohesiveness as a tendency that an agent tries to get similar knowledge with other agents. Each agent has a cost function (G_i) based on both the knowledge heterogeneity among the agents who are connected directly and change of fitness of their own knowledge.

In the previous study, 'insulation' was known to limit the scope of information that the organizational members can access (Flippen, 1999). So, we assumed that 'insulation' is the degree (θ) to which the external factors such as information, metric, knowledge and norm are blocked. The type of 'leadership' is represented by manipulating the influence (h_{sup}) between the hierarchies which is mentioned above, and 'homogeneity' is determined by an initial state of organizational knowledge. Finally, 'Lack of norm and procedure' was controlled through the time (τ) of the organizational decision-making process.

3.3.1.1 Process overview and scheduling

The model proceeds in unit time step that all agent decide their next behavior. Within each period, four modules are processed following order: Initialization, Reference model, Antecedent model, Reference model and Save and exit. Intialization module consists of two functions, which are importing packages and generate random agents, parameters and data frame to store the interim findings. In the reference model module, the agents decided their future behaviors and update the individual knowledge, performance and diversity. This module is iterated until the period to predefined maximum iteration . Parallel with the reference model, the antecedent module is implemneted when cpature the effect of antecedents of groupthink. The last module is save and exit module that upload the dataframe storing the interim findings on the data repository. In addition, all simulation models in this study are developed by Python 3.5

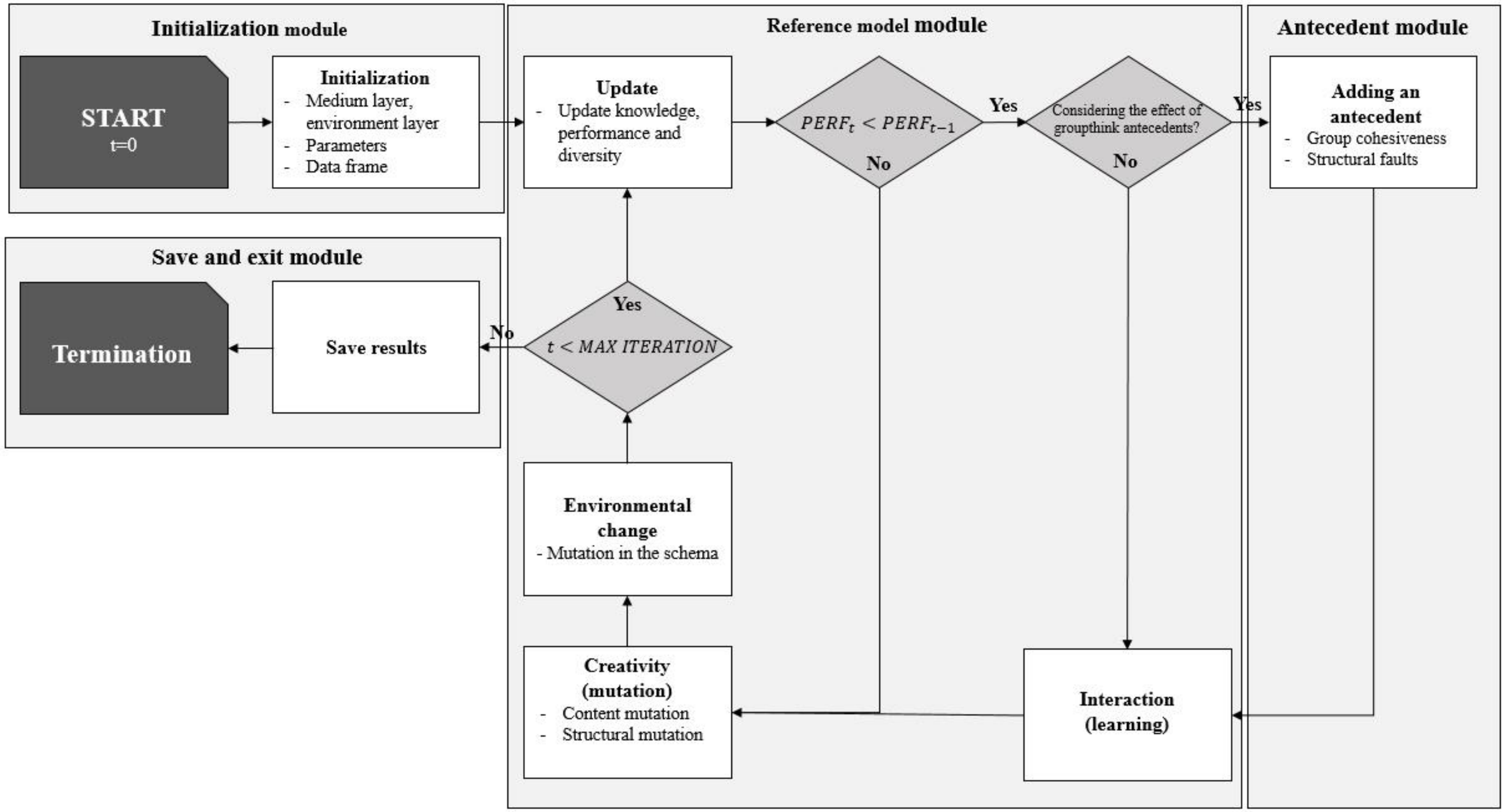


Figure 12. Self-organization groupthink model process

3.3.2 **Design concept**

Emergence: This study focuses on the organizational level emergences which is generated by behaviors and interactions of the agent layer. On the perspectives of the organizational performance and diversity, self-organization emergence can be observed.

Adaptation: Since the performance of each agent determined by the fitness with the schema, agents explore the optimal knowledge through trial and error. During this procedures, the agents choose better behavior based on their individual performance changes. Also, they try to learn another's knowledge to improve the individual performance. Consequently, both the organizational knowledge and individual knowledge can approach to the schema which is the optimal solution.

Fitness: Under the limited network, the agents cannot explore the entire space of solution set. So, they calculate their own performance based on the previous performance. In other words, the agents perceive their own performance relatively rather than an objective figure. Therefore, the fiteness-seeking is an implicit process in this study. *Prediction:* The agents in this ABM can't expect the changes of environment. They only depend on the previous experiences to decide the next state which are maintaining the incumbent knowledge or change it.

Sensing: The agents sense their own status based on the previous performance.

Interaction: The agents can interact with the other agents who are in one links on the predefined network. If two agents are directly connected, they can learn another's knowledge. During the learning process, learning capability and hierarchy determined the performance and direction of learning.

Stochasticity: All agents are assigned random parameters by specific distributions. Also, the learning process is based on the probability of learning capability, and the creativity depends on the probability of creativity involving the mutation of structure and content.

Collectives: Individual agent has neighborhood on the social network, and they can interact with those neighbors.

Observation: This study observes the result in two ways. The organizational performance is measured by fitness function mentioned before, and the diversity is calculated based on the Euclidian distance between two different knowledge landscapes which is composed of vectors.

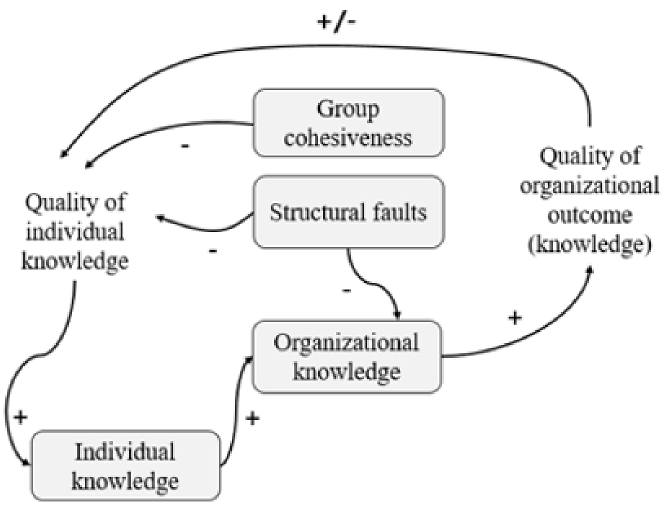


Figure 13. Relationship between the variables and states

3.3.3 **Details**

3.3.3.1 Initialization

Each ABM simulation was initially occupied with randomly generated agents and their social network involving the organizational hierarchy which is predefined. Both agents and their network have random parameters to reflect the heterogeneous aspect of individuals. The starting point of each ABM simulation assume a certain time that an organization set a goal to be achieved. This goal is represeted by a form of schema (Haupt & Haupt, 2006; Simon, 1996). The evaulation of each simulation run began from the first period when the agents and their network were constructed. This study measure the result of ABM simulation based on two asepects: Organizational performance and Diversity.

3.3.3.2 Input

In all ABM simulations, the parameters of agent were generated by a uniform distribution between 0 and 1. The detail ranges of each parameter referred to the settings of the previous studies (see table 13). Also, the individual knowledge landscape followed the uniform distribution function which has boundary value as the initial heterogeneity (Var_{ini}). The initial number of agents are 100 and the maximum iteration number is 100. The social network of agents is a random newtwork which have network density ($\rho_{i,j}$) as 0.3. To compare the individual performances at the first period, each agent has an initial value for criteria which has a random number between 0 and 1.

3.3.3.3 Sub-models

(1) No interaction model

Before testing the antedents of Janis' groupthink model, we should determine a reference model to compare the simulation results. The first sub-mode, "no interaction model", is determined by individual traits such as learning capability and creativity. In other words, each agent can compare their performances but they only depend on self-modification of knowledge. Since the interaction between the agents are not conisdered, we can capture the effect of utility maximization behavior.

(2) Interaction model

The second simulation model is the ‘interaction model’ which adds cooperative behaviors into the no interaction model. There are various intra-organizational interactions based on the type of organization. However, our research model focuses on the knowledge collaboration process based on ‘learning’ and ‘compromise’. Such interactions are the processes to approach the ideal knowledge through intellectual exchanges. So, we can predict the effect. This model was utilized as a reference model of this study.

(3) Groupthink models

As mentioned before, five antecedents of groupthink will be tested in this ABM simulations. The impact of each antecedent included in the reference model. Group cohesiveness model assume that the agent considers the homogeneity of organization than their own performance. Insulation model has a probability to change organizational schema by the intervention of outer-group. Homogeneity model divided into high homogeneity and low homogeneity model. Lack of procedures (or norms) model assumed an early termination of organizational concurrence-seeking process. The leadership model reflected the increased level of directive leadership. Detail configurations of these models is described in table 14.

This study represents the result of the ABM simulation involving the organizational performance and diversity through the comparison among the sub-models mentioned above. The detail results will be shown in the next section.

Table 12. Brief description of components in ABM simulation

Layer	Variable	Definition	Measurement	Notation	Reference
Environment layer	Organizational performance	alignment with their environment to achieve long term survival and growth (Fiol et al., 1985)	$Y(X) = \frac{1}{m}\sum_{i=1}^{m} {\delta_i}^2$, $0 \leq Y(X) \leq 1$	$Perf_{org}$	March (1991) Posen, Lee, & Yi (2013)
	Diversity	Different behavior patterns of agents (Holland, 1995)	$\mathrm{D(X,Y)} = \sqrt{\sum_{i=0}^{N}(x_i - y_i)^2}$ $Div_{org} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\mathrm{D}(\mathrm{X}_i, \mathrm{Y}_j)}{2 \times m}$	Div_{org}	Yeokeun Kim (2011)
	Network density	Mean intensity or strength of ties of joining alters (Marsden, 1987)	$\text{adjacency} = \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix}$ $\sim\rho_{i,j} = 0.3$	$\rho_{i,j}$	Bienenstock, Bonacich, & Oliver (1990)
	Knowledge heterogeneity	The degree of dispersion of individual knowledge	$Var_{ini} = 50$	Var_{ini}	-
	Hierarchy	Learning capability from the agent in lower hierarchy	$h_{sup} \sim Uniform(0.1, 0.5)$	h_{sup}	-
	Iteration	Number of simulation iteration	$Max\_iter = 100$	Max_iter	-
State	Initial	Criteria for performance	$P_i^{initial} \sim uniform(0,1)$	$P_i^{initial}$	-

variable	performance	comparison at the first period			
	Maintaining	Maintaining the existing behavior if the current performance is higher than before	Performance at t $\geq$ Performance at t-1	*model*=0	LeBaron (2000), North, Macal, & Campbell (2005), Silveira, Espíndola, & Penna (2006)-
	Modifying	Maintaining the existing behavior if the current performance is lower than before	Performance at t < Performance at t-1	*model*=1	
Medium layer (agent)	Number of agent	Total number of agents generated at the initial stage	m=50	m	-
	Learning capability	A probability to replicate another's knowledge	$\mu_i \sim Uniform(0.1, 0.9)$	μ_i	March (1991)
	Collaboration	A probability to interact with the other agents	f_{col}~Uniform(0,1)	f_{col}	Prindle & Hasty (2010)
	Creativity	Random mutation of knowledge landscape	π_i, C_i,~Uniform(0,0.2)	π_i C_i	March (1991),Haupt & Haupt (2006)
	Schema	Optimal knowledge landscape to which the organization aims but does not know.	$Knw_{schema} = [(a_1, w_1), \ldots, (a_k, w_k)]$ $a_i \sim N(0,10)$	Knw_{schema}	McHugh et al. (2016).

	Individual knowledge	A knowledge landscape that an agent possess at period *t*	*a*: attribute of knowledge *w*: weight of knowledge Knw_i=$[(a_1, w_1), \dots, (a_k, w_k)]$ $a_i \sim Uniform(-\frac{1}{2} \times Var_{ini}, \frac{1}{2} \times Var_{ini})$	Knw_i	McHugh et al. (2016).
	Organizational knowledge	A knowledge landscape that an organization possess at period *t*	$Knw_{org} = [(a_1, w_1), \dots, (a_k, w_k)]$	Knw_{org}	McHugh et al. (2016).
Antecedent of groupthink	Cohesiveness	The total field of forces that act on members to remain homogeneous in the organization (Casey-Campbell & Martens, 2009)	Argmin $G_i = \frac{1}{m}\sum \mathrm{D}(x_i, x_j)$, i and j are adjoining	Argmin G_i	Moorhead and Montanari (1986)
	Insulation	Intervention of external parties	$\theta = 0.3$	θ	Janis(1972), McCauley(1998)
	Leadership	The level of directive leadership (Breitsohl et al., 2015; Fodor & Smith, 1982; Leana, 1985; Maciuliene & Skarzauskiene, 2016)	$h_{sup} \sim$Uniform(0.5,0.9)	h_{sup}	Cruz, Henningsen, & Smith (1999)

	Lack of procedure (norm)	Procedure refers to a guideline for good decision (Rajakumar, 2019)	$\tau = Max\_iter/2$	τ	Callaway, Marriott, and Esser (1985)
	Homogeneity	The level of similarity among the agents' background knowledge and experience (Flippen, 1999)	$Var(Knw_i)$=100	$Var(Knw_i)$	Rajakumar (2019)

Table 13. Initial configuration of each experiment

Factor	Notation	Experiment models						
		Reference	Group cohesiveness	Insulation	High homogeneity	Low homogeneity	Lack of norms and procedure	Directive leadership
Cohesiveness	G_i	$\Delta perf_{i,j}$	$\Delta Var(knw_{org})$	$\Delta perf_{i,j}$	$\Delta perf_{i,j}$	$\Delta perf_{i,j}$	$\Delta perf_{i,j}$	$\Delta perf_{i,j}$
Insulation	θ	0.3	0.3	0.0	0.3	0.3	0.3	0.3
Homogeneity	-	~N(μ,σ²), $\{0 \le \mu \le 10,\ \sigma^2 = 100\}$			~N(μ,σ²) $\{0 \le \mu \le 100,\ \sigma^2 = 200\}$	~N(μ,σ²) $\{0 \le \mu \le 100,\ \sigma^2 = 50\}$	~N(μ,σ²), $\{0 \le \mu \le 10,\ \sigma^2 = 100\}$	
Max_iter	τ	100	100	100	100	100	50	100
Leadership	h_{sup}	~U(0.1~0.5)	~U(0.1~0.5)	~U(0.1~0.5)	~U(0.1~0.5)	~U(0.1~0.5)	~U(0.1~0.5)	~U(0.6~0.9)
Hierarchy of organization	$r_{sup,k}$	$r_{sup,0} = 0.7,\ r_{sup,1} = 0.2,\ r_{sup,2} = 0.1$						
Network	$p_{i,j}$	0.3						
Learning	μ_i	~U(0.1,0.9)						
Collaboration	f_{col}	~U(0.1,0.9)						
Creativity	π_i,C_i	~U(0,0.2)						

3.4 Simulation results

The present study experimented with the types of ABMs. The first model, “no interaction model,” makes an organizational decision without any interactions with the agent. In this model, the organizational performance or groupthink phenomenon depends on individual properties such as learning capability or creativity. From these experiments, we can capture the role of individual traits in a group decision-making process. The second model is the “interaction model” and includes cooperative behaviors. This is the most well-known form of the simulation model and involves a number of interactions. It is also an ideal model for an organization that does not have any groupthink antecedents. The last model is the “groupthink model” which considers the antecedents of Janis’ groupthink model. We identified the impact of each antecedent on groupthink and organizational performance in this model. However, since it is hard to examine all potential correlations among the antecedents, we assumed that each antecedent was mutually independent during the experiments. Each type of simulation model was repeated 100 times to confirm the reliability of our ABMS, and all results including those on organizational performance, knowledge distribution, and variance were computed based on the arithmetic mean of accumulated experiments. ....

3.4.1 No interaction model

The “no interaction model” is determined by individual traits such as learning capability and creativity. In this model, even if all agents do not interact with other agents, they can evaluate their knowledge using the cost function G_i. When the value of G_i increases, the agent can try to change their own knowledge and vice versa.

Figure 13 shows the changes in the landscape of organizational knowledge by time and the shape of ideal knowledge called schema. Organizational knowledge has maintained a shape similar to that of the initial state. Performance and deviation of knowledge are presented in figure 14. That there were no significant changes in the results pertaining to organizational performance during the experiment is obvious. Although we found that the deviation of organizational knowledge decreased gradually, the absolute variation in knowledge deviation was relatively small.

From the results of the "no interaction model," we suggest two conclusions. First, individual rationality does not matter in group decision-making. Second, individual efforts without interaction are hard to bring up to a certain level of concurrence during the decision-making process. Thus, when an organization relies only on individual competence, not only does the degree of concurrence stay at a low level, but there is also no improvement in the organizational performance.

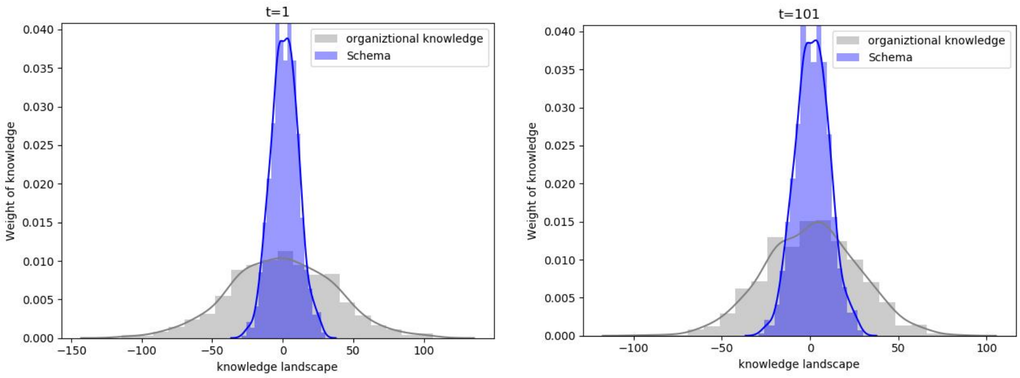
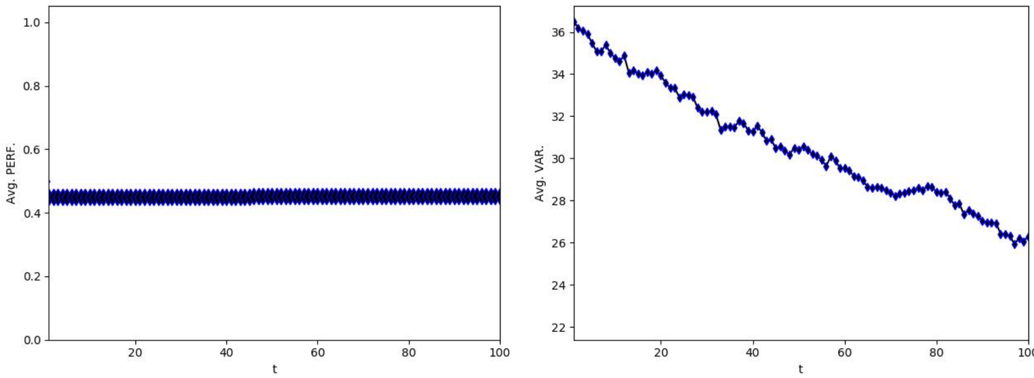


Figure 14. Average knowledge landscape of 'No interaction model'



Performance **Variance**

Figure 15. Average performance and variance of 'No interaction model'

3.4.2 **Interaction model (baseline model)**

The second simulation model is the "interaction model" which adds cooperative behaviors into the "no interaction model." There are various intra-organizational interactions based on the type of organization. However, our research model focuses on the knowledge collaboration process based on "cooperation" and "compromise." Cooperation is a process to approach the ideal knowledge through intellectual exchanges. Contrary to cooperation, compromise can be used by agents when the ideal knowledge is hard to find, or the goal is not specified. So the agent in a compromise situation should set in place some "average knowledge" based on the neighborhood, and adopt it as an alternative idea.

The results of the "Interaction model" clearly show different patterns from those of the "no interaction model." As seen in figure 15, organizational knowledge converges to a certain point on the knowledge landscape. When the organizational knowledge converges, the shape of the knowledge landscape is sharpened. At the 100th period, we found that the unit knowledge of organization concentrated on a certain point like a delta function. From the changes in the knowledge landscape, we found a tendency of organizational concurrence. Figure 16 provides a more concrete evidence of concurrence-seeking and organizational performance. The performance of the organization rapidly increased in the early stage and then converged at a certain point and stabilized at that level of performance. We also found that even after the increase in organizational performance stopped, the variation in knowledge continued to decrease. In other words, the consensus may be an unnecessary process after the organizational performance reaches a certain level. This redundant concurrence-seeking is similar to the groupthink phenomenon (Janis, 1972; McCauley, 1989).

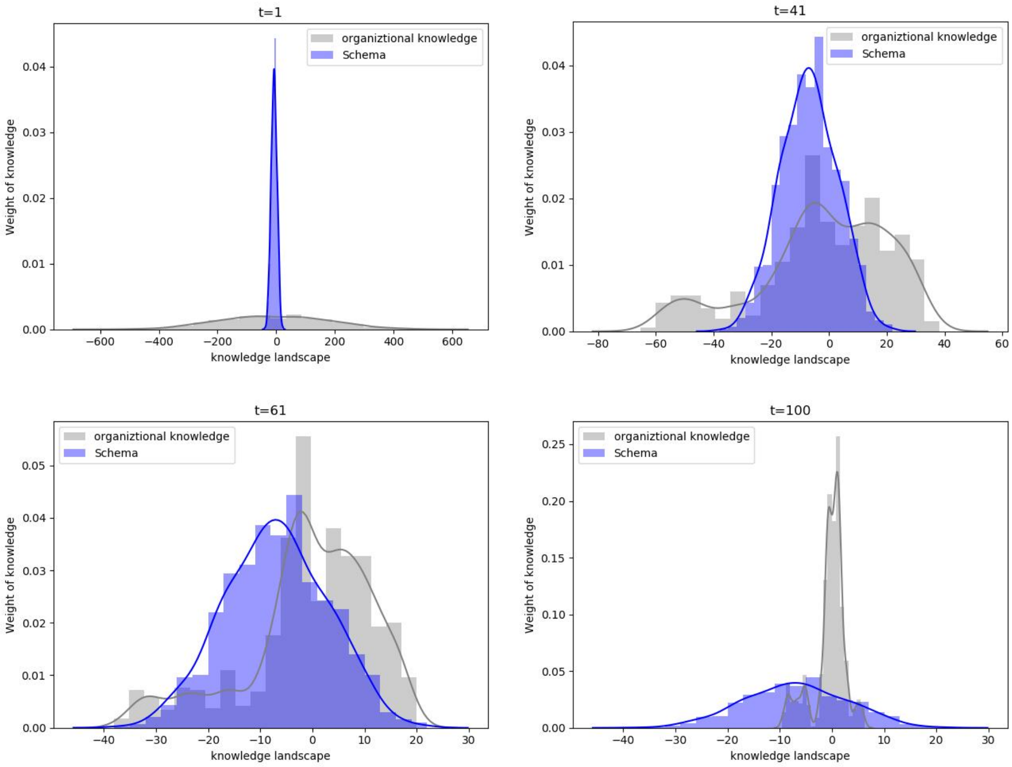
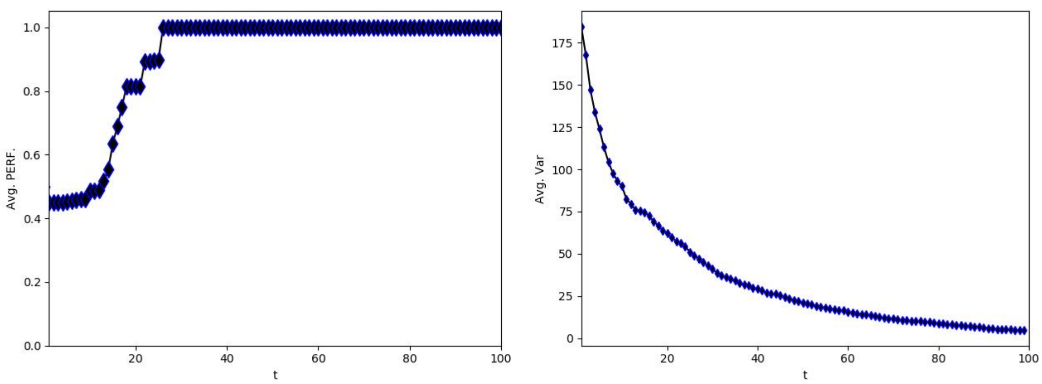


Figure 16. Average knowledge landscape of 'Interaction model'



Performance **Variance**

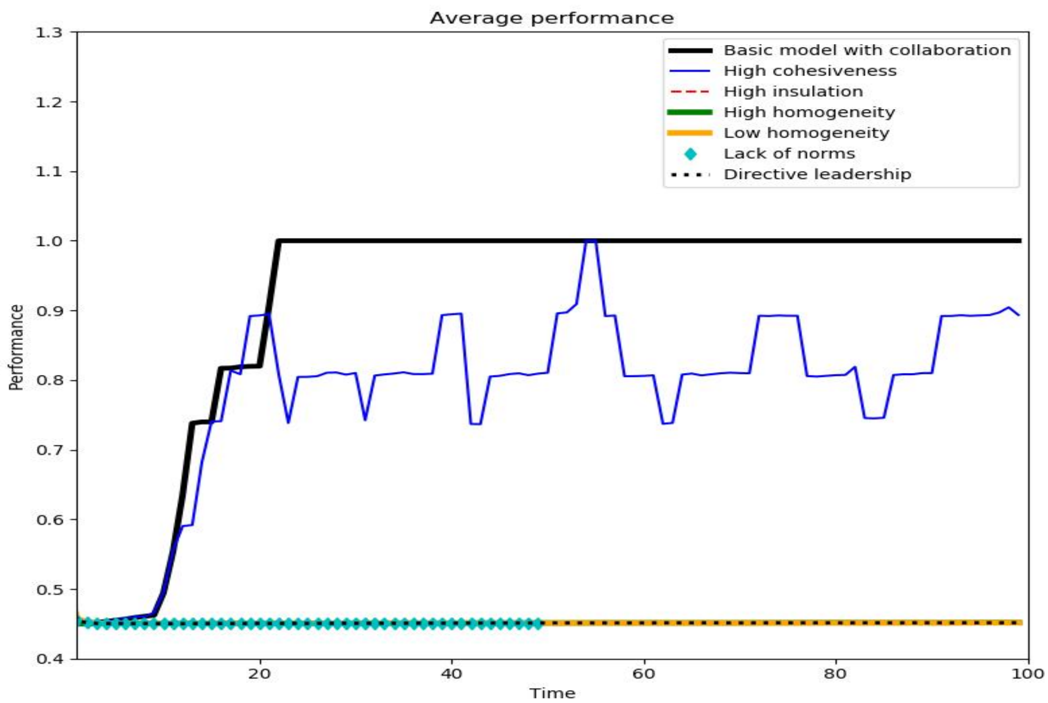
Figure 17. Average performance and variance of 'Interaction model'

3.4.3 Groupthink models

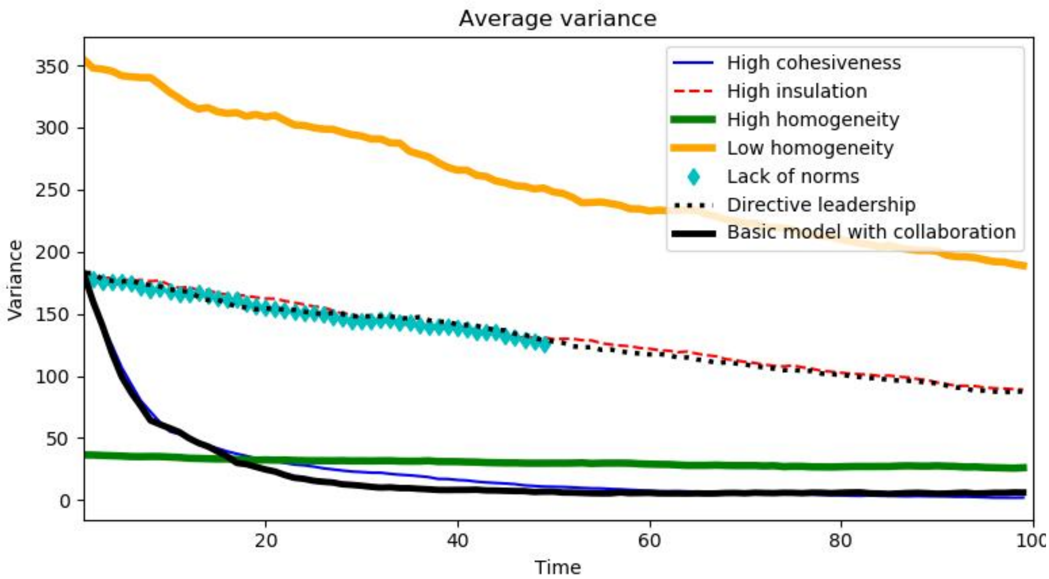
The initial configuration of the groupthink model is presented in table 4. As mentioned above, our research model assumes that there is no mutual correlation among the groupthink antecedents. Therefore, we operated sequential and independent experiments with the effects of each component of the antecedents.

Figure 17 presents the average performance and variance of each model involving a specific factor. At first, the plot at the bottom of figure 17 says that cohesiveness significantly decreases the variance of organizational knowledge. These effects of cohesiveness correspond with Janis' groupthink model on the point that the cohesiveness may lead to the groupthink phenomenon (Brockman et al., 2010). However, contrary to Janis' model, we found evidence for the positive influence of groupthink on the quality of outcomes (Gully et al., 1995). According to the first plot in figure 17, high cohesiveness induces higher performance, as opposed to the situation in other models where structural faults are included. At the same time, we can observe a fluctuation in organizational performance with time. High fluctuations in organizational performance present a trend that is different from the pattern that emerged from "collaborations." Although this difference is not fully explained by Janis' groupthink model, it is possible to deduce that the process of "collaboration" is different from that of "cohesiveness."

Different from cohesiveness, the other factors that are called "structural faults" in Janis' groupthink model did not present any notable consequences both in terms of organizational performance and variance. The second plot in figure 17 which magnifies the left side performance plot shows that the result of the organizational performance presents very few changes over 100 periods. We were thus able to capture that the structural faults have not changed the performance of the organization from its initial state. Further, the plot of average variance in figure 17 proves that even though there was a decrease in the variance of knowledge, the extent of those changes is too small to support the existence of an organizational consensus. These results contradict the assumptions in Janis' original model.



Average performance

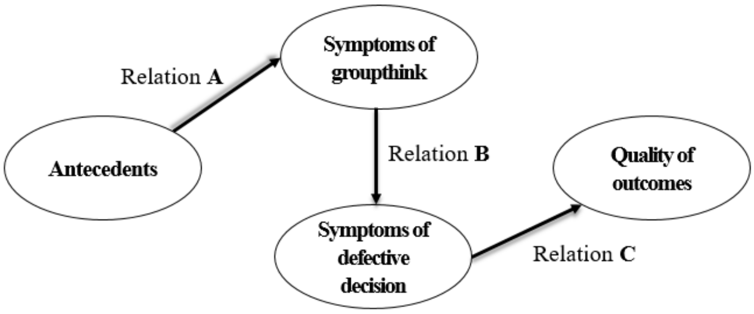


Average variance

Figure 18. Performance and variance of groupthink model

3.5 Discussion

We conducted two analyses to test Janis' (1972) groupthink model. The first analysis was based on the individual survey of the members of the organization. SEM analysis shows that only one assumption relevant to the causality between antecedents and groupthink phenomenon assumed in Janis' groupthink model is supported. According to this result, the antecedents enhance the likelihood of the emergence of the groupthink phenomenon (Janis, 1972). On the contrary, there is no meaningful relationship between groupthink and the quality of organizational decision-making, thus this result suggests the possibility that groupthink may not become an organizational fiasco. This result is contradictory to existing studies that have emphasized the negative effects of groupthink. Consequently, the results of SEM analysis are beneficial in understanding the groupthink phenomenon and may provide evidence of studies that oppose Janis (1972&1982). However, it is insufficient to fully describe either the underlying mechanism or the dynamics of the groupthink model. There is also the point that the prerequisites and symptoms of groupthink are difficult to measure in external approaches such as surveys (W. Park, 1990). Thus, we additionally constructed an ABMS and experimented with several models not only to test Janis' groupthink model but also to suggest new perspectives. Repeated simulation experiments have allowed us to draw some new conclusions from our ABMS.



Relation	Structural equation model	Agent based model simulation
A	Positive effect	• Cohesiveness: positive effect • Structural fault: weak effect
B+C	No effect	• Cohesiveness: positive effect • Structural fault: no effect
A+B+C	No effect	• Cohesiveness: positive but fluctuant • Structural fault: negative

Figure 19. Comparison of two analyses

We constructed three types of simulation models: “no interaction model,” “interaction model,” and “groupthink model.” The “interaction model” is a baseline for the “groupthink model.” In the “groupthink model,” we added group cohesiveness and structural faults to test the effects of the antecedents on groupthink and the quality of the outcomes. We drew three interesting conclusions through the groupthink model.

3.5.1 The effect of group cohesiveness

First, group cohesiveness not only enhances organizational performance but also leads to concurrence-seeking in the organization. Different from the baseline model, the simulation model involving group cohesiveness presents a pattern that repeats the rise and fall of organizational performance. These fluctuating performance changes can be explained based on the complex adaptive perspective. The baseline model preserves and exchanges individual knowledge through a process called “collaboration” as mentioned in the previous chapter. Furthermore, it makes an alternative by using the knowledge recombination process to adapt to its environment. However, cohesiveness makes people compliant with other people’s ideas or opinions of their colleagues rather than recombining their own. Since the compliance of members limits the diversity of organizational knowledge, the spectrum of knowledge narrows down with time (J. Esser, 1998; I. L. Janis, 1982; Massari et al., 2019). Loss of diversity can enhance resilience toward environmental changes (Fang, Lee, & Schilling, 2010; Han, 2017) and limit the source of creativity (Fang et al., 2010) and innovation (Obeid, 2015; Woerter, 2009) of an organization. When there is no intervention from the external environment, cohesiveness is an efficient way to achieve organizational goals. However, when fluctuations in the environment require ideas that are out of the existing spectrum, homogeneous organizations encounter difficulties in adapting to a new environment. As a result, time delays will occur while creating a different knowledge set that fits into the changed environment. The average performance plot in figure 17 presents this fluctuation. In summary, although group cohesiveness clearly has a positive influence on the quality of outcome, the organization cannot cope quickly with environmental changes when group cohesiveness exists alone because of the lack of preserved knowledge diversity. Therefore, the classical hypothesis that cohesiveness can be a source of groupthink was supported, but the causality between cohesiveness and organizational outcome quality is still doubtful. Rather, our ABMS results support the claim that collective cohesion improves the level of group performance.

3.5.2 The effect of structural faults

Second, four variables called structural faults including insulation, leadership, homogeneity, and lack of norms and procedures have insignificant effects on the groupthink phenomenon. As shown in the average variance plot in figure 17, the relative change in knowledge diversity is significantly less than that of the cohesive or baseline model. We can observe the decrease in organizational knowledge variance, but it is too small an amount to argue that there is a significant relationship between the structural faults and groupthink. On the other hand, structural faults inhibit the enhancement of organizational performance. According to the results of the "groupthink model" experiment, compared to the baseline model, each factor among the structural faults appears to hinder the quality of group decision-making. Although the performance of the organization did not decrease further than the initial point, we can conclude that structural faults did act as a factor to exacerbate both the process of group decision-making and the performance, when seen as a competitive situation. Structural faults influence the quality of organizational outcomes negatively rather than bring about a groupthink phenomenon.

3.5.3 Inevitability of groupthink

Finally, from the baseline model, we can capture concurrence-seeking as shown in figure 16 and 17. Janis' groupthink model argued that concurrence-seeking is a "pre-stage" of groupthink which is caused by antecedents such as cohesiveness, structural faults, and provocative context. According to our ABMS results, the antecedents of groupthink are not the only root causes for concurrence-seeking. Other factors except groupthink antecedents can be determinants of concurrence-seeking and groupthink, too. Cooperative behavior, noted as “collaboration” may be an alternative factor to lead concurrence-seeking in an organization. This means that any organization can also confront the groupthink phenomenon regardless of the existence of antecedents. Consequently, groupthink may be a natural phenomenon of an organization with cooperative behaviors rather than a special issue emerging from certain factors or situations.

Table 14. Summary of the content of analyses

Model		Goal	Main result
Structural equation model analysis		Testing Janis groupthink model	- Antecedents cause groupthink phenomenon - Groupthink phenomenon doesn’t influence to the quality of decision-making
ABMS	Basic model-I	Effect of individual rationality	- Learning behavior doesn’t effect on groupthink - Learning behavior doesn’t effect on the organizational quality of decision-making
	Basic model-II	Effect of intra-organizational interaction	- Interaction among the organizational members leads concurrence seeking tendency - Interaction among the organizational members increase the quality of organizational decision-making
	Groupthink model-I	Effect of group cohesiveness	- Cohesiveness leads groupthink phenomenon - Cohesiveness increase the quality of decision-making temporarily - High cohesive group requires some time to adapt to the changing environment than ‘Basic model II’

Chapter 4. Comparing the better knowledge creation strategy of organizations in groupthink situations

4.1 Introduction

In the early studies on the organizational knowledge creation, organizational knowledge is a something discovered rather than be generated (R. Davis, 1986; Yoon & Kerschberg, 1993). So, the role of individual is more emphasized, even in the knowledge management area (Nonaka, Von Krogh, & Voelpel, 2006b). Also on the epistemological perspective, knowledge was defined as a justified belief of individual, in other words, knowledge had been considered as ‘pre-given’ or ‘already exist’ (Nonaka, 1991). However, since ICT widened the scope of communication, people have been exposed to a larger amount of knowledge through knowledge transfer, sharing, recombination (Robertson et al., 1996). At ths same time, as the problems and their solutions gradually had become huge and complex, knowledge creation get more difficult to be taken by the small number of experts and individuals. As a result, organizational knowledge began to be considered as a potential alternative embracing the problems of modern society. Nowadays, the value of knowledge has been increased unprecedentedly in most social organizations such as industry, public sector, and our daily lives (Liebowitz, 2001). Knowledge management has provided a basic framework for transforming individual knowledge into organizational knowledge known as collective intelligence.

Response to the social needs of organizational knowledge, previous literature have tried to find effective way to creat organizational knowledge. The concept of collective intelligence was proposed in this context. Different to the prior theories, the organizational knowledge shows the better performance in terms of collective intelligence (Maleewong, Anutariya, & Wuwongse, 2008; Surowiecki, 2004; Yun & Lee, 2011). This advantage of collective intelligence leads to the amount of researches on how to create organizational knowledge effectively (e.g., Curşeu, Jansen, & Chappin, 2013; Engel et al., 2014; A. W. Woolley et al., 2010; Anita Williams Woolley, Aggarwal, & Malone, 2015). Exsiting theories for collective intellignece emphasizes two major asepect of organization. First, interactions among the individuals is necessary for creating organizational knowledge and collective intelligence utlimately (Hernández-Chan et al., 2016; Massari et al., 2019). Second, diversity has been suggested as another determinant of collective intelligence (Maciuliene & Skarzauskiene, 2016; Massari et al., 2019; Täuscher, 2017; A. W. Woolley et al., 2010). Therefore, previous studies have pointed out that interaction and diversity are the key factors of collective intelligence.

Despite several determinants of collective intellligence were uncovered, there is still unsolved old problem related to groupthink. However, in terms of organizational strategy, there are few studies dealing with how to transform groutphink into collective intellgience. In other words, we can distinguish groutphink and collective intelligence, but we do not clearly understand the correlation between them.

Interestingly, previous studies have tried to figure out the links between groupthink and collective intelligence in various ways (e.g., Jafari et al., 2015; Solomon, 2006; Erdem, 2003, Reia et al., 2019). These studies proposed similar factors to induce collective intelligence, which are diversity (e.g., Aggarwal & Woolley, 2013; Ellis et al., 2003; Hinsz, Vollrath, & Tindale, 1997; Kozhevnikov, Evans, & Kosslyn, 2014; Malone & Bernstein, 2015; Massari et al., 2019; Schut, 2010; Solomon, 2006; Spielman, 2014b; Surowiecki, 2004; Anita Williams Woolley et al., 2015a) and interaction (e.g., Furtado et al., 2010; Hernández-Chan et al., 2016; Hwang et al., 2009; Maciuliene & Skarzauskiene, 2016). So it can state that two groups of study mentioned above share common foundations even though their topics are different.

Unfortunately, previous study This study pays attention to this. However, divesity and interaction are too abstract in terms of the practical usage. So, the studies including the factor on the strategic level were investigated. From those studies, three common startegic factors were derieved: (1) knowledge conflict have been considered as not only a solution of groupthink (e.g., Ferraris & Carveth, 2003; Flippen, 1999; Gully et al., 1995) but also a determinant of collective intelligence (e.g., Barki & Hartwick, 2004; Chiocchio, 2007; Malone & Bernstein, 2015). (2) Reconsideration of alternatives also one of the major solution for groupthink (e.g, Chapman, 2006; I. L. Janis, 1982) and the source of collective intelligence at the sametime (e.g., De Vincenzo et al., 2018; JafariNaimi & Meyers, 2015; Solomon, 2006). (3) Organizational memory is metioned in both area which are solution for groupthink (e.g., Barki & Hartwick, 2004; Casey-Campbell & Martens, 2009) and source of collective intelligence (Bieber et al., 2002; Hinsz et al., 1997; Reia et al., 2019). If groupthink can be changed to collective intelligence, the main problem is how to do it. As mentioned above, groupthink and collective intelligence are similar in the perspective of their mechanism. Thus we guessed that the intersections between two phenomena are able to be a source of interconversion. The previous studies of the groupthink and collective intelligence presented that there were three common factors in preventing the groupthink and promoting the collective intelligence.

The goal of this study is finding out the way how to transform groupthink into collective intelligence. This study is for answering to two questions. First question is 'which factors can improve the quality of organizational knowledge under the groupthink situation?' and 'what is the optimal strategy of utilzing switching factor?'. For the first question, we defined 'switching factors' which are common factors including both the solution of groupthink and source of collective intelligence, and proposed the role of each factor. As the answer to the second question, this study conducted the efficiency analysis based on 8 strategy models including switching factors. In this study, these strategies are designed based on the combination of switching factors and compared by output efficiency relative to input of an organization in terms of organizational knowledge creation. So, through this step, this study can answer to the question 'how to use switching factor to improve the qualtiy of organizational knowledge'.

In the first step, this study collected two kinds of literature, grouthink and collective intellignece, and find out the common factors appearing simulataneously in both groups.

Based on the result of comparisons, we defiend three switching factors of collective intelligence: knowledge conflict, reconsideration of alternatives and organizational memory. Also, in order to identify the characteristic and role of each switching factor, we developed an agent-based model. Through the ABM simulations, the effect of switching factors on the way how to optimize organizational knowledge and biasedness of organizational knowledge.

Based on the result of the first step, we developed 8 strategic group by the combination of switching factors. Since it is difficult to compare each strategy without common criteria, this study adopted a concept of meta-frontier efficeincy usually utilized in comparing relative efficiency among heterogeneous groups (O'Donnell et al., 2008). For the meta-frontier analysis, this study generated virtual dataset from the ABM developed in the first step. In this study, virtually generated dataset is seperated by involvement of switching factors included in a certain simulation. The result shows that the combination of knowledge conflict and reconsideration of alterantive shows the highest efficiency, but the group soley adopting reconsideration of alterantive result in the lowest efficiency.

Considering the result of this meta-frontier analysis, the contribution of this study is providing a guideline for designing organizational strategy to improve the quality of knowledge. This is crucial for not only organizations which are suffered from fiscoes of groupthink, but also organizations that want to transplant collective intelligence into them. In additional to this, this research has an academic novelty in terms of methology. Generally, applying parameters derieved from the empirical analysis to the ABM simulation is common way to combine two methodologies. However, the opposite cases are rare, because the result of ABM is not represent a certain value of real world excatly. Because of this problem, direct comparison of ABM simulation results often insufficient for testing its validity.

The outline of this study is following steps: Section 4.2 introduces literatures for detail understanding of theoretical background. Section 4.3 presents ABM as a research model and section 4.4 compare the efficiency of organizational knowledge creation using dataset generated by the ABM in section 4.3. Section 4.4 provide discussion of the MFA results and section 4.5 conclude with practical implication and limitations.

4.2 Effect of switching factor

An ABM is an effective analytical tool for explaining complex social phenomena involving numerous and individual interactions and represents a number of computational simulations generated from the agent who is predefined by the decision making rules (Klimek, Poledna, Doyne Farmer, & Thurner, 2015). In fact, ABM is more of a paradigm of perspective than an analytical tool (Bonabeau, 2002). Generally, ABM was used to analyze complex and large systems through a set of independent objects (Epstein & Axtell, 1996; Gilbert & Troitzsch, 2005; Holland, 1995; LeBaron, 2000; Miller & Page, 2007). Although repeated interactions, competition, and learning among agents in the simulation process are common, their forms vary depending on detailed rules, the nature of objects, the way they interact, the structure of the connection, and so on. Expanding the scope, models for most complex systems, such as genetic algorithm and Cellular automata, can fall into the category of ABM. Thus, the flexibility and scalability of ABMS can address problems that other methods, such as demonstration models, statistical models, and surveys, cannot solve, especially problems such as mitigation of strict assumptions, controls in individual level, and simplification (Rand & Rust, 2011). Arbitrary organization subject to this study is also a large system consisting of individual entities, within which various kinds of interactions occur. In addition, computational methodologies have been pervasively used for solving and optimizing complex phenomenon of collective intelligence (Lykourentzou et al., 2011). Thus, to represent and analyze the research question, ABM can be an appropriate analytical tool and is effective in achieving the objectives of the study.

4.2.1 **Overview**

4.2.1.1 Purpose

The research model agrees with the stream arguing that groupthink is an emergence rather than a result of linear causalities (McCauley, 1998; Riccobono et al., 2016). The perspective of complex adaptive system (CAS) is suitable to handling emergent phenomenon. That's why this study adopted the ABM simulation method to understand the effect of switching factors in organizations.

4.2.1.2 Variables and functions

The ABM of this study was designed as two layers involving the agent layer and the environment layer. The agent layer denotes a set of agents who interact with other agents and determine future behaviors based on the collected information. The environment layer provides external conditions indicated by predefined parameters and defines rules for agents and the entire system. Also, another major role of this layer is to be a window for observing the emergences.

(1) Agent layer

The ABM of this study was designed as two layers involving the agent layer and the environment layer. The first layer is the agent layer referring to persons belong to an organization. The agents of this layer have four common characteristics: autonomy, interdependence, rule compliance, and adaptation (Macy & Willer, 2002). The agents with these characteristics can create patterns by local and global interactions which is a self-organization system (Kaufman, 1996). This study developed the agent who meets these characteristics.

Since individual knowledge is created by fragmented information, its interpretation and combination (McHugh et al., 2016), knowledge can be defective and uncertain (R. Davis, 1986). This study describes individual knowledge (knw_i) as a distribution of 'unit knowledge (k_n)' consisting of the location(x_n) and weigt (w_n).

$$knw_i = [k_1, k_2 \dots k_n], k_n = (x_n, w_n)$$

Individual knowledge can be changed by two factors: first, interactions among the agents can change the shape of knowledge distribution and second, time increases the uncertainty of knowledge. According to Gardiner (2009), the change in the knowledge distribution is explained by a stochastic differential equation called the Langevin equation . The Langevin equation provides an insight for describing the change of probability distribution depending on time. If we assume that the location of the agent is *x*, according to the equation, the changes of location can be expressed by the sum of the deterministic and stochastic terms. Thus, the differential of *x* can be derived from a deterministic location ($a(x,t)$) and the drift term ($b(x,t)$) with noise (ξ).

$$\frac{dx}{dt} = a(x,t) + b(x,t)\xi(t),\ \ \xi(t) \sim \text{random walk}$$

Assuming the current location (x) is a random variable, the above equation is represented as follows (detail derivation is in appendix 9).

$$knw_i^t = A\left(knw_{j(i\neq j)}^{t-1}\right) + \xi(t)B(knw_i^{t-1})$$

In this equation, drift term, $A\left(knw_{j(i\neq j)}^{t-1}\right)$, means that the expected location at *t*-1 and $B(knw_i^{t-1})$ denoting a stochastic turbulence term at *t*. This equation means that the knowledge distribution at *t* is calculated by deterministic information and stochastic noise.

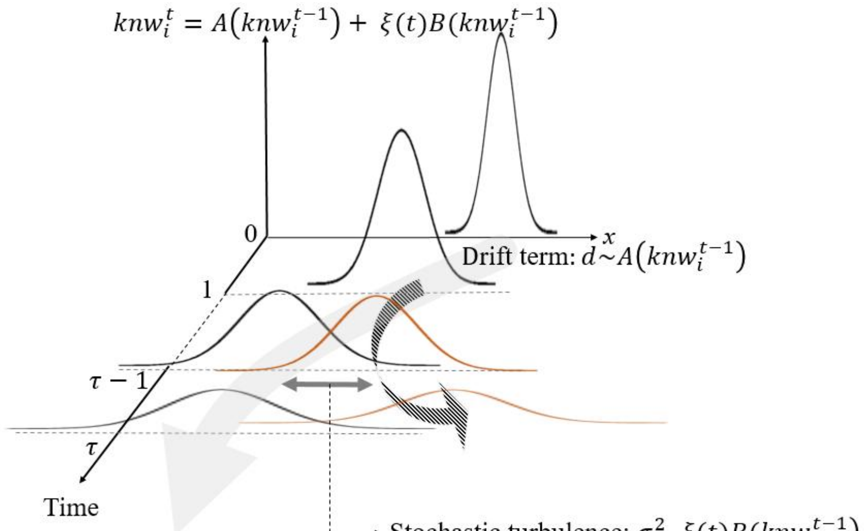


Figure 20. Visual description of the drift term and stochastic turbulence of knowledge distribution

This knowledge distribution is formed by random parameters derived from a certain distribution. Each agent have an unique values referring to the deviation of knowledge distribution (σ_i), and average location (μ_i) of individual knowledge.

In the agent layer, arbitrary agent i attempts to make decisions to enhance the utility determined by their perceived performance ($p_{ind,i}$), because the agents can not recognize exact value of their own utility. Before deriving the percevied performance, a form of utility function should be defined. This study adopted a logarithmic utility function known as more effective than a quadratic form when expressing the behaviors of people, especially (Kraus & Litzenberger, 1975). Cobb-Douglas utility funciton is a special form of logarithmic utility function, and it is postulated as a standard utility function (Voorneveld, 2008). Also, this form of utility function well describes myopia behaviors of people (Feldman, 1992) and interaction between the inputs. Thus Cobb-Douglas untility function has been frequently used for expressing individual utility in studies using ABM methodology (Bredin, Kotz, & Rus, 1998). Our utility function is composed of two variables; qaulity of individual knowledge and quality of organizational knowledge.

Self-centeredness (α_i) and sensitivity (K) are adopted to reflect the heterogeneous personality of agents. In this function, self-centeredness refers to the degree to which individual knowledge is more important than the quality of organizational knowledge. Conventional ecnonmics supports the idea that individuals are rational and has selfish tendency, however selfish taste based prediction can be falsified when the individuals have another motivations (Bethwaite & Tompkinson, 1996). Dambrun & Ricard (2011) explained the situation coexisting different motivation through the concept of self-centeredness. Self-centeredness is defined as exaggerated importance given to self by comparing various motivations (Dambrun & Ricard, 2011). To represent this concept, this study adopted an exponential term which has been used in Cobb-Douglas utility function. Sesitivity means the coefficient of individual and organizational performance to the level of utility. In the original Cobb-Douglas function, total-factor productivity (TFP) had meausred the ratio of aggregate output (eg., GDP) to aggregate inputs (e.g., labor, capital, technoloy)(Sickles, R., & Zelenyuk, 2019). However, at the level of personal utility, TFP represents the ratio between the source of utility (e.g., performance) of the utility. That is, at the individual level, this exchange rate refers to a perceived sensitivity of his or her performance to the utility, which is a unique parameter of each agent. Thus, the utility function of each agent is defined as:

$$U_i = K_i \ Q_{ind,i}^{\alpha} \ Q_{org}^{1-\alpha}$$

Based on this utility function, each agent can determine their behavior for the next period. In order to capture the performance of current behavior, the utility of adjacent agents on the social network is required. Each agent compares its own utility with the neighborhood's based on a relative ranking of utility. This study assumed that when the rank of an agent's utility is under the middle among the adjacent agent, the agent will change behavior. If an agent tries to change the incumbent behavior, the agent is in the active state. On the contrary, when the agent tries to stay on the existing position, we can say that it is in the inactive state.

However, it is difficult to know their own utility exactly. So people recognize their own utility through the relative rank of individual utility (Arentze et al., 2013). Thus, the individual performance (p_{ind}) is defined as a relative rank ($Rnk_{i,t}$) of individual utility among neighborhoods.

$$p_{ind,i} = 1 - \frac{Rnk_{i,t}}{Number\ \ of\ \ neighborhoods\ \ at\ \ t}, p_{ind,i} \in (0,1)$$

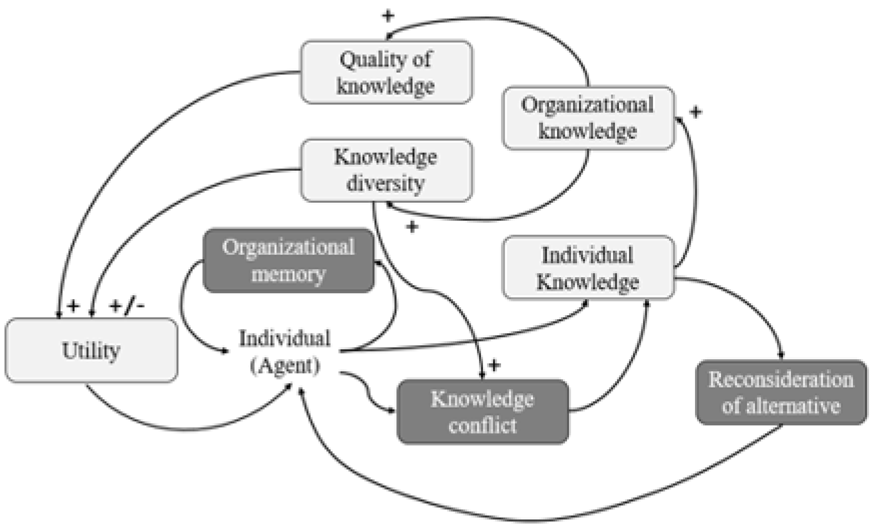


Figure 21. Relationship between components of the ABM

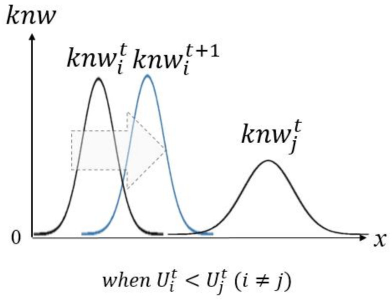
Table 15. Variables of agent layer

Variable	Definition	Reference
Knowledge distribution Unit knowledge	Distribution of 'unit knowledge' $knw_i = [k_1, k_2 \dots k_n]$ $k_n = (x_n, w_n)$, x_n: *location of* k_n; w_n: *weight of* k_n	McHugh et al. (2016)
Utility function	Logarithmic utility function of organizational member based on individual performance and organizational performance $U_i = K_i \; P_{ind,i}^{\alpha} \; Q_{org}^{1-\alpha}$	Kraus and Litzenberger (1975), Bredin et al (1998)
Self-centeredness	The degree to which individual knowledge is more important than the quality of organizational knowledge (α)	Dambrun & Ricard (2011)
Sensitivity	A perceived sensitivity of his or her performance to the utility (K_i)	Sickles, R. and Zelenyuk (2019)
Knowledge deviation	Deviation of individual knowledge of agent *i* (σ_i),	-
Knowledge location	Average of individual knowledge of agent *i* (μ_i)	-
Perceived performance	Performance that an agent perceives based on relative rank of utility $p_{ind,i} = 1 - \frac{Rnk_{i,t}}{\#\ of\ neighborhoods\ at\ t}$	Arentze et al. (2013)
Neighborhood	A list of adjacent agents *Neighbor* = $[a_1, a_2 \dots a_n]$	-
Rank	Rank of individual performance among the neighborhoods ($Rnk_{i,t}$)	-
State	Current state of each agent	-
Noise	Random number generated from Wiener process ($\xi(t)$)	Gardiner (2009)
Drift term	Direction of shift of knowledge distributions ($A\left(knw_{j(i\neq j)}^{t-1}\right)$)	Gardiner (2009)

(2) Environment layer

The second layer is the environment layer. Despite the environment layer not having the authority to intervene in the behavior of agents, it can affect the agent indirectly (Cha et al., 2019). In this layer, there are two essential pieces of information influencing the behavior of the agent. First, organizational performance is an important signal. This information is calculated by comparing the organizational knowledge with the predefined solution-set called "fitness" in the evolutionary computation (Levitt & March, 1988; J.G. March, 1991). Second, this layer defines the environmental conditions where the agent belong. The initial condition is invariant if there is no external impact.

The learning process has been considered as one of the basic interactions to improve organizational performance (e.g., Levitt and March, 1988; Posen et al., 2013). Despite imitating different knowledge, it is the most well-known method (Gilbert & Terna, 2000). However, it is too simple to describe interactions between the distributions of individual knowledge. Thus, we represent the learning of knowledge distribution as a stochastic drift. To reflect the stochastic drift, we assumed that the agent wants to get closer to other agent's knowledge who have higher utility. As mentioned above, the accumulated information of shift is in $A\left(knw_j^{t-1}\right)$ term. Thus, we can denote the stochastic drift as the expected location term.



$$A(knw_i^{t-1}) = \begin{cases} E(knw_i^t) + |u(t)|\theta\left[knw_j^t - knw_i^t\right], when\ \ U_i^t < U_j^t \\ E(knw_i^t) + u, U_i^t \geq U_j^t \\ 0 \quad if\ \ agent\ \ i\ \ is\ \ isolated \end{cases}$$

$$i \neq j;\ \ u{\sim}U(0,1);\ \ \theta(Z)\ \ refers\ \ to\ \ sign\ \ of\ \ Z$$

Figure 22. The learning process of individual knowledge distribution

The last role of the environment layer provides the outcomes of the system. Since groupthink and collective intelligence are patterns rather than events (Turner & Pratkanis, 1998c), it is hard to observe them on the intra-organizational level (Park, 1990; Turner and Pratkanis, 1998). Therefore, the transformation of groupthink can be observed on the environment layer. To discover large-scale patterns, we observed the shape, bias, quality of organizational knowledge, and average utility.

Organizational knowledge (knw_{org}^t) is described as a merged knowledge distribution of individual's knowledge distributions with a total area of 1.0. The knowedge distribution is represented by a set of vectors involving the location of unit knowledge and their weight. The quality of knowledge (Q_t) is calculated by comparing the organizational knowledge (knw_{org}^t) with the optimum knowledge (knw_{opt}).

$$knw_{org}^t = \frac{1}{N}\sum_{i=1}^{N} knw_i^t\ , N\ \ is\ \ number\ \ of\ \ agent$$

$$Q_t = 1 - \frac{1}{m}\left|knw_{opt} - knw_{org}^t\right|$$

Environment layer also includes parameters to define the structure and characteristics of an organization, for example number of agent, network structure, simulation duration and volume of knowledge distribution.

Table 16. Variables of environment layer

Variable	Definition	Reference
Number of agent	Total number of agent generated at each simulation (*N*)	-
Simulation duration	The number of iteration of each simulation (max_iter)	-
Volume of knowledge	The number of unit knowledge in each knowledge distribution (k)	-
Network density	A probability that an agent connect to another agent (ρ_t)	Newman (2010)

(3) Switching factor

In the literature review chapter, I introduced three switching factors transforming groupthink into collective intelligence. Knowledge conflict is rooted from the task conflict (Barki & Hartwick, 2004). Different to the relational conflict, task conflict has focused on the background knowledge, perception, perspective or opinion (Karen A. Jehn & Mannix, 2001). Jehn (1995) argued that task conflict can increase the organizational performance through three kinds of interactions: Combination, mutual learning and enhancement. So, this study denoted the knowledge conflict as a knowledge learning process between the most heterogeneous agents. The heterogeneity ($H_{i,j}$) between the two different agent i and j is calculated as the sum of the unoverlapped areas of knowledge distribution held by each agent. Also, knowledge conflict can occur regardless of the network structure.

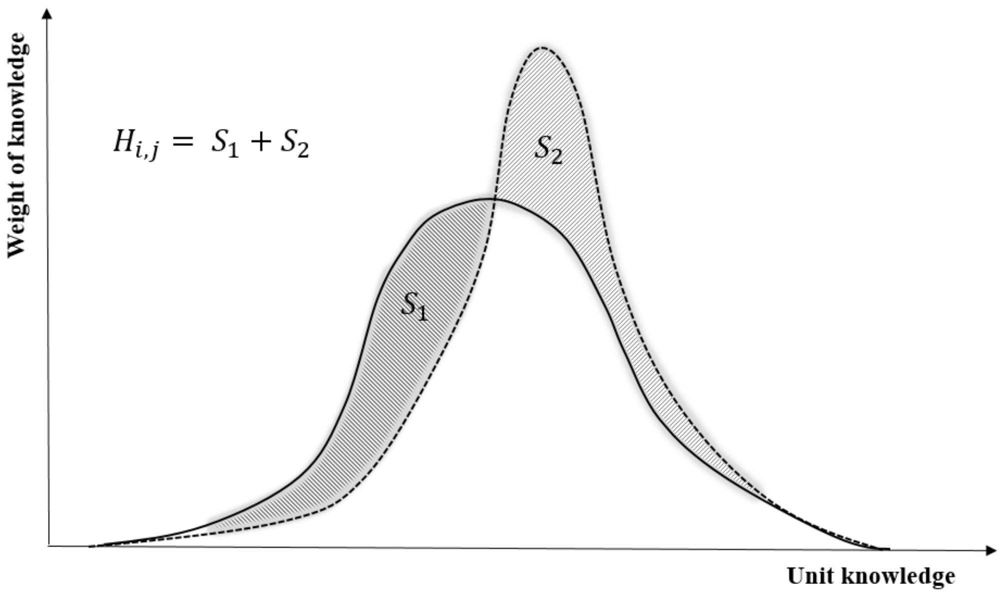


Figure 23. Calculation of heterogeneity between two knowledge distributions

Reconsideration of alternative is a factor of the agent layer. In the previous groupthink studies, reconsideration had been conceptualized as the quantity of reconsideration (e.g., Breitsohl et al., 2015; Courtright, 1978; Ferraris & Carveth, 2003; Flippen, 1999; McCauley, 1989; Montanari, 1986; W. Park, 1990). Especially, Esser, (1998), Janis and Mann (1977) and Montanari (1986) suggested that even already failed alternatives should be reconsidered to overcome groupthink phenomenon. This study represent the reconsideration of alternatives as increasing the possbility to interact with low performed agent and decreasing the probability of learning from the high-performed agents. In the reference model, the agent only learns from another which have higher performance with a certain probability (π_{low}), but the reconsideration model assumed that agents can learn from the lower performance agent with a probability of π_{low}. This is the type 1 reconsideration. Also, since the agent can only perceive relative performance not the exact level of performance, each agent can not distiguish the best performer. So, type 2 reconsideration refers to that the agent learns equally from the higher performance agents. Organizational memory require the organizational system storing and retriving knowledge (Walsh & Ungson, 1991). Spender (1996) argued that organizational memory requires the learning process, and also emphasized that learning and memory are funtionally equvalent in terms of the organizational knowledge. In other words, organizational memory learn (store) knowledge from an individual or organization. Thus, in this study, the organizational memory was desgined that it accumulate individual knowledge randomly at the every time step, and individual agent can access them to learn at them same time. From these assumptions, we can define three parameters: storing, retrieval and decay rate. Storing (π_{store}) refers to a probability that a certain knowledge of agent at period t is stored in organizatinal memory, and retirieval (π_{retrv}) refers to a probility to access organizational memory to learn the stored knowledge. Also, stored knowledge can be distorted because knowledge can be forgotten or decayed as time goes. So the decay rate (π_{decay}) refes to a possibility to change a stored knowledge randomly.

Table 17. Variables of switching factor models

Variable	Definition	Reference
Heterogeneity	Difference between two knowledge distributions ($H_{i,j}$)	-
Type 1 reconsideration	Reconsideration of failed alternatives (π_{low})	Janis and Mann (1977), Park (2000)

Type 2 reconsideration	Reconsideration of ignored alternatives (π_{high})	Flippen (1999), Janis (1982), McCauley (1998)
Storing	Storing a certain individual knowledge to organizational memory (π_{store})	Walsh & Ungson (1991)
Retrieval	Retrieving any stored knowledge by learning (π_{retrv})	Walsh & Ungson (1991) Spender (1996)
Decay rate	Distortion of stored knowledge over time (π_{decay})	Tunney (2003), Reber (1989)

4.2.1.3 Process overview and scheduling

The ABM simulation of this study consists of 3 steps following the orders: updating information, interaction and messurement. At the updating information, all values including parameters, variables, and states are renewed based on the previous simulations. This process should be handled first because it is a ground of next decisions and behaviors by agents. Iteraction step is a main process of this ABM simulation. This step includes actual decisions of agents and interactions based on the predefined rules consisting of functions and parameters. The last step is the measurement stage where observes emergence in terms of knowledge quality, knowledg bias and average utility of agents. This three process are repeated until the current period exceed the maximum iteration value. All the ABM simulations will follow the same process explained above. Figure 27 shows the ABM simulation process of this study. Each iteration in the ABM simulation does not equivalent to the sequential time concept. As mentioned before, this ABM simulation adopted the asynchronous framework. Thus one iteration of simulation just refers to that all agents choose their new state and modify their own behavior accordingly. In addition, all simulation models in this study are developed by Python 3.5.

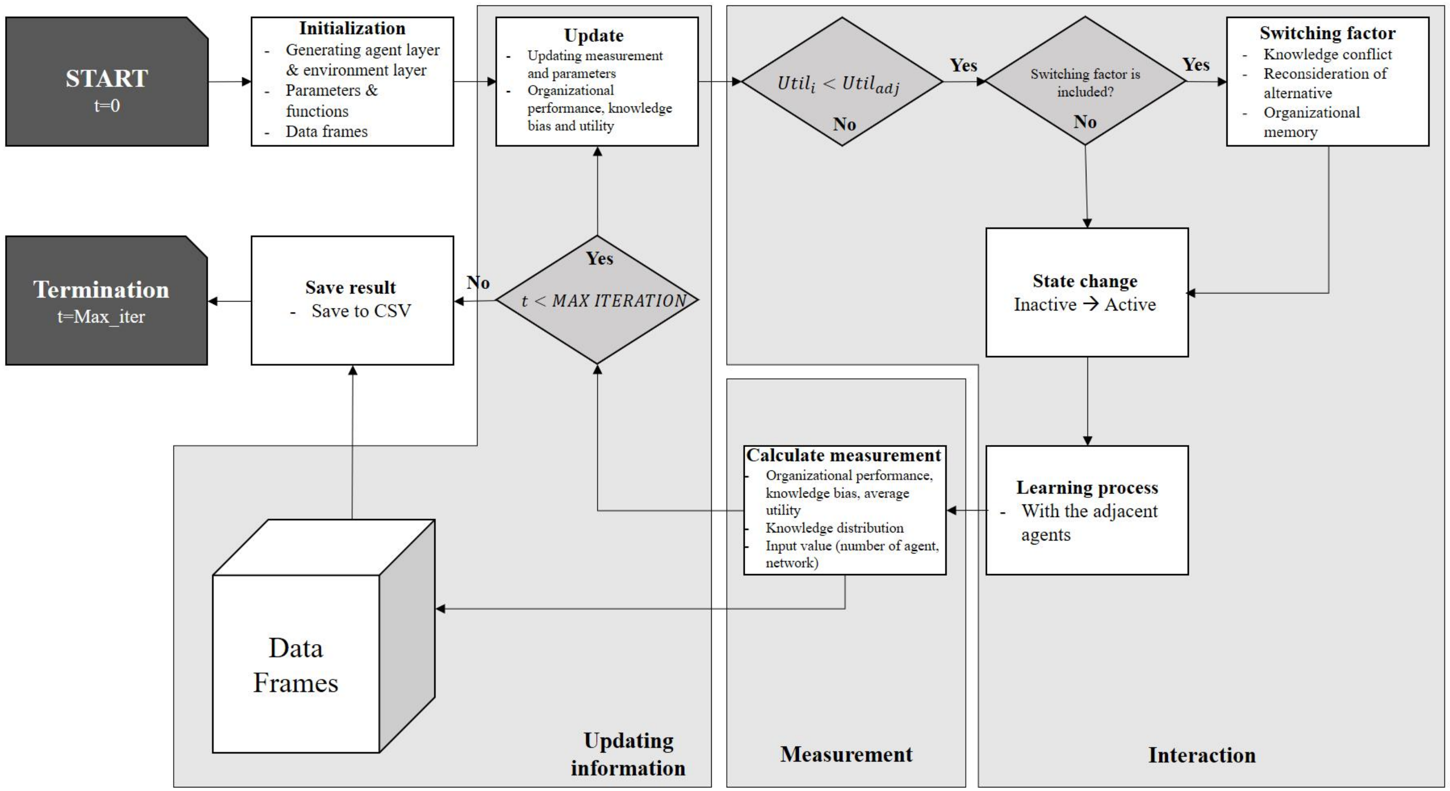


Figure 24. Process of ABM simulation

4.2.2 **Details**

4.2.2.1 Initialization

Each ABM simulations were conducted with generating agent and environment layers. The beginning point of simulation was equivalent to the time when the optimal knowledge is defined by the goal of organization. This means that all agents did not have any preliminary information about the optimal knowledge. Thus this study assume that individual knowledge is dispersed uniformly at a certain level of variance (Var_{init}). Indeed, regardless of the form of individual knowledge, organizational knowledge follows a form of normal distribution because of the central limit theorem.

The results of simulations are calculated after a certain iteration. Basically, this ABM has two loops: Inner loop and outer loop. Inner loop refers to the progress of an ABM simulation, and outer loop plays a role to conduct the entire simulation repeatedly to acquire the average values for simulation results, such as the quality of knowledge, knowledge bias and average utility of an organization. Each simulation assumed the same number of agent (*N*), iterations (max_iter) and network structure. Network of agents is a random graph with a certain average centrality (ρ_t)

4.2.2.2 Input

To conduct ABM simulations, parameters of each model should be defined before generating two layers. In this study, there are three kinds of parameters. First group is the parameters requiring a certain value given by external source at the initialization, such as number of agent, simulation duration, network density, volume of knowledge, self-centeredness, sensitivity. Also, initial state of each agent should be defined by random selection. The second parameter group represent variables or state that updates itself after the initial value setting. This group involves knowledge distributions and state. The last group of parameter is that calculated or derived automatically under the given condition which comes from the first and second group of parameters. In this group, all measurements including performance, utility, neighborhood, rank, knowledge location and deviations and functions do not request any external inputs. Therefore, we only need to be consider putting the initial values in the first and second group of parameters. The initial value and the setting of the range referred to the relevant study as much as possible, and if there is no previous study or their details are neglected, the scope was assumed to be as wide as possible. The initial inputs and their ranges are described in table 19.

Table 18. Initial inputs of ABM simulation

Variable		Initial value	Reference
Global parameters	Number of agent	50	March (1991)
	Simulation duration	100	-
	Experiment iteration	100	-
	Volume of knowledge	100	Koohborfardhaghighi & Altmann (2017)
	Network density	0.3	Newman (2010), March (1991)
	Network reorganizing	0.1	Koohborfardhaghighi & Altmann (2017)
	Agent state	*active*	-
Utility	Self-centeredness	$\sim U(0.5,1.0)$	Dambrun & Ricard

			(2011)
Knowledge distribution (individual)	Sensitivity	~*U*(0.1~1.0)	-
	Average location	~*U*(0,40)	-
	Deviation	~*U*(1,25)	-
Knowledge distribution (optimal)		~ N(0,5)	-

4.2.2.3 Sub-models

Except the reference model, there are three sub models for capturing the effect of switching factor, and four additional models including multiple switching factors for comparing the organizational efficiencies. The properties of each sub-models are in table 20.

Table 19. Description of sub- models

Model		Component	Knowledge conflict	Reconsideration	Organizational memory
Reference model	Sub-model 1	Reference model	X	X	X
Single-factor model	Sub-model 2	Knowledge conflict	○	X	X
	Sub-model 3	Reconsideration of alts.	X	○	X
	Sub-model 4	Organizational memory	X	X	○
Multi-factor model	Sub-model 5	Knowledge conflict, Reconsideration of alts	○	○	X
	Sub-model 6	Reconsideration of alts., Organizational memory	X	○	○
	Sub-model 7	Knowledge conflict, Organizational memory	○	X	○
	Sub-model 8	Knowledge conflict, Reconsideration of alts., Organizational memory	○	○	○

4.3 Simulation result

4.3.1 Reference model

To analyze the effect of switching factors, the reference model is tested. Output of the reference model can provide criterion to compare the results of the other experiment models. In addition, since robustness of the ABM simulation is a critical issue, a sensitivity test was conducted (Pannell, 1997). Homma & Saltelli (1996) suggest that the robustness of a model can be verifiable by a scatter plot of output; this study follows that method. Figure 25 shows the results of the sensitivity analysis. According to these results, our research model seems consistent enough on the fluctuation of inputs.

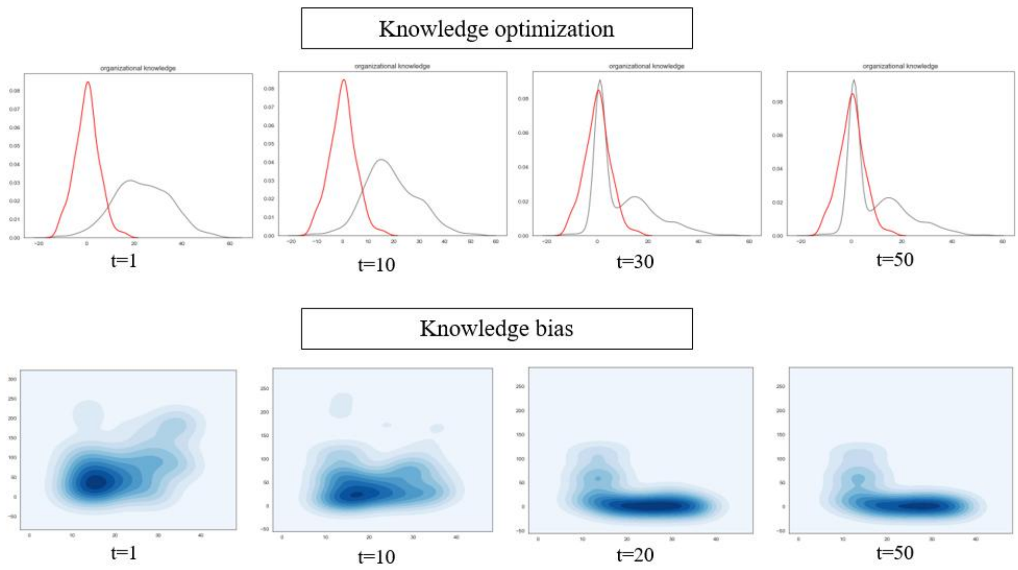


Figure 25. Result of the reference model

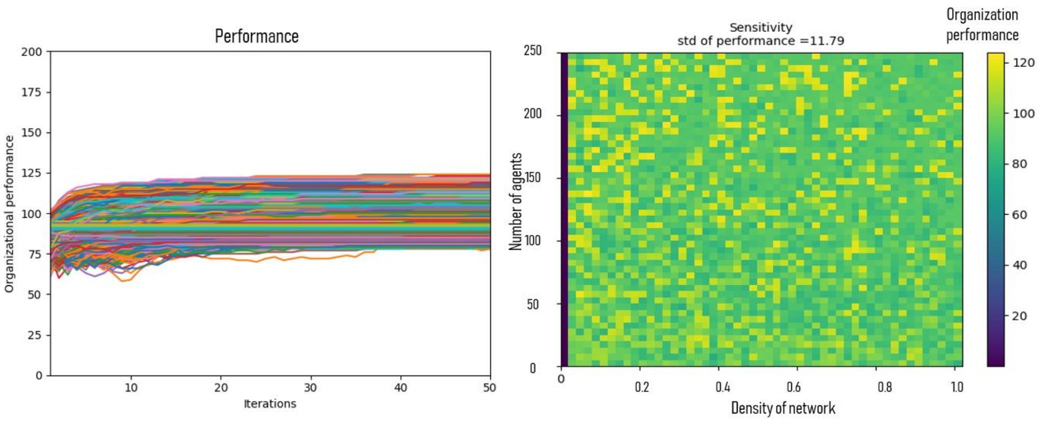


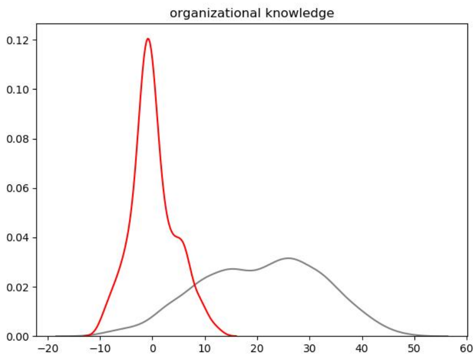
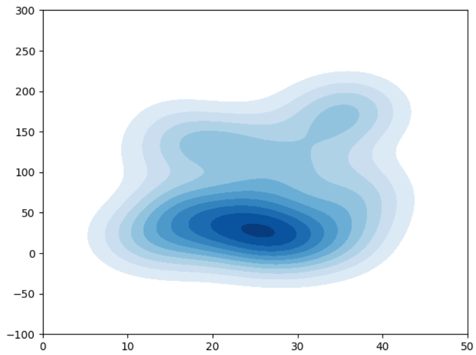
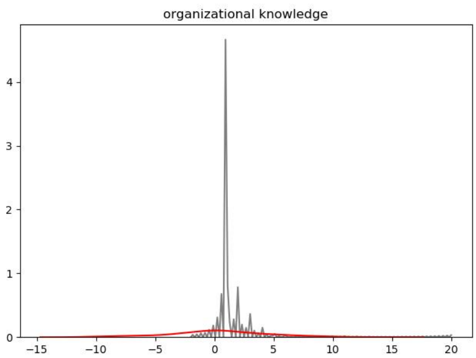
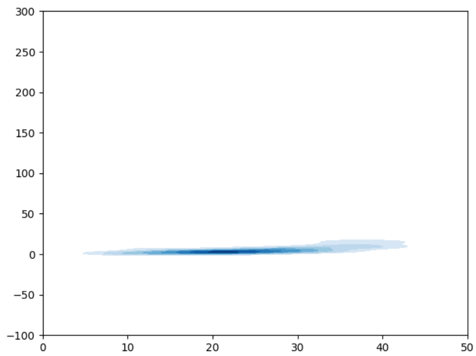
Figure 26. Result of sensitivity test

4.3.2 Knowledge optimization and knowledge bias

As mentioned above, this study assumes three switching factors to resolve the groupthink phenomenon. The first switching factor is knowledge conflict. In this study, knowledge conflict is defined as combining knowledge of two agents, i and j, who have a high heterogeneous score $(H_{i,j})$. Two interacting agents are determined by the score of heterogeneity defined as follows:

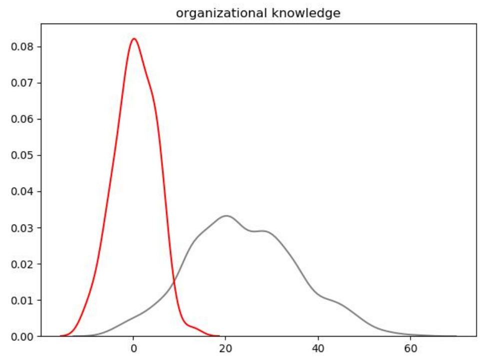
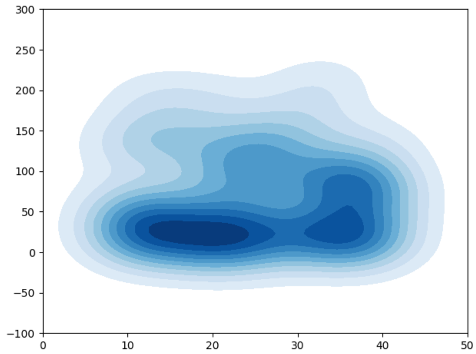
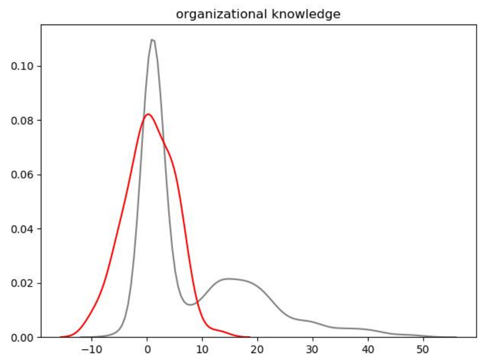
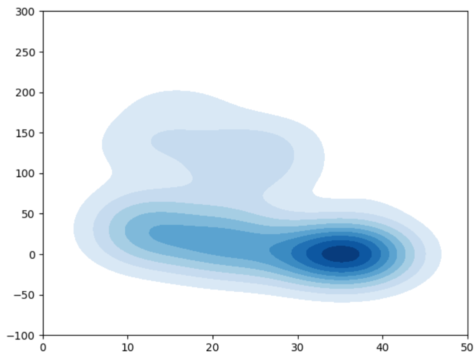
$$H_{i,j} = \int [knw_i(t) - knw_j(t)]$$

Table 20. Effect of postponing decision making

t	Knowledge optimization	Knowledge bias
	: Solution set : Organizational knowledge	High density Low density
1		
100		

The second factor is reconsideration of alternatives providing additional chances for exploring better solutions. To reflect the reconsideration on the ABM simulation, each agent is assigned a probability that they will delay learning the other agents' knowledge. This delay allows them to consider the existing knowledge before adopting the another's knowledge.

Table 21. Effect of reconsideration of alternatives

t	Knowledge optimization : Solution set : Organizational knowledge	Knowledge bias High density Low density
1		
100		

Not only existing knowledge, but also obsolete knowledge can be exploited usefully during the organizational knowledge creation process. That is why organizations store their knowledge in an explicit form. The stored knowledge can be mutated in many ways when people retrieve it based on their individual context, such as background knowledge, experience, and prejudice (Gammelgaard, 2010; Ikujiro Nonaka, 1994). Also, the content of knowledge can be distorted if that knowledge is not used for a long period of time. In this analysis, all created knowledge should accumulate in organizational memory and the knowledge (k_i^t) created by agent i at time t is randomly mutated based on the temporal distance ($d = t - t_0$) from the time it was stored (t_0).

Table 22. Effect of organizational memory

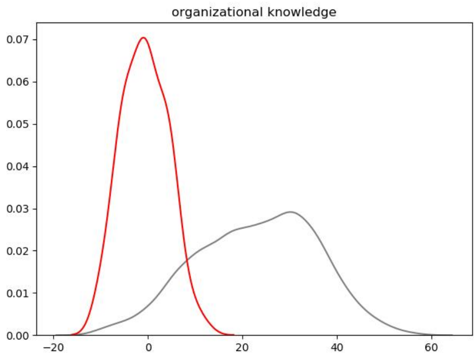
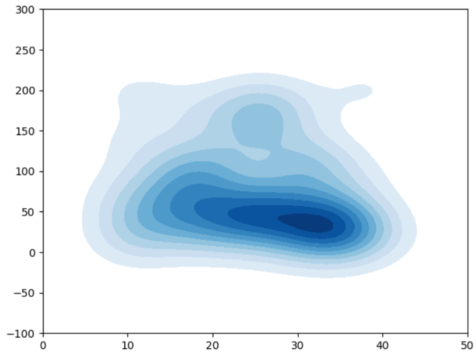
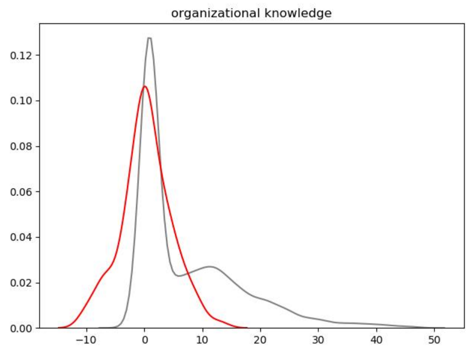
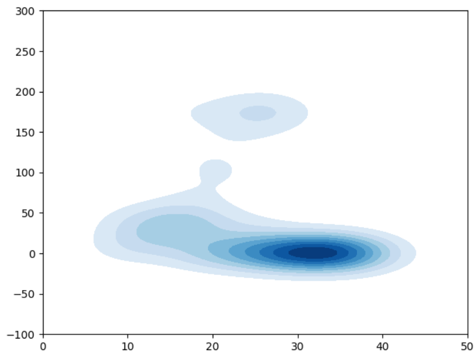
t	Knowledge optimization	Knowledge bias
	: Solution set : Organizational knowledge	 High density Low density
1		
100		

Table 21,22,23 include the results of knowledge optimization and bias. The organizational knowledge optimization results describing how the organizational knowledge and the optimal solution set are similar and the knowledge bias refers to how individual knowledge is dispersed. From these two aspects, we observed that all of three switching factors may enhance the fitness to the optimal solution set. Knowledge conflict especially makes individual knowledge dramatically converge within the optimal knowledge set. On the aspect of knowledge bias, the switching factors have no effect on decentralizing individual knowledge. In fact, the knowledge conflict and organizational memory increases it. A point of interest is that the organizational memory forms an island-like area of individual knowledge over time.

Despite the status of knowledge optimization and bias briefly describing their influence, it is not certain they are able to transform groupthink into collective intelligence. As mentioned previously, groupthink and collective intelligence cannot be identified until they produce final outcomes. Thus, the quality of organizational knowledge and the average utility of agents are calculated to compare the performance of the final outcomes.

4.3.3 Quality of knowledge and average utility

Through three simulation experiments, this study captures the effect of each switching factor on the quality of organizational knowledge and the average utility of agents. Since the dominant difference between groupthink and collective intelligence manifest in the quality of their final outcomes (Hansen & Vaagen, 2016; Täuscher, 2017), higher performances in both the organization and individual may guarantee collective intelligence rather than groupthink.

Figure 27 shows that knowledge conflict (experiment 1), as a switching factor, significantly increases both the organizational performance and individual utility. Knowledge conflict encourages repeated organizational conflict, but before there are sufficient interactions, it can lead to an inefficiency of collective intelligence. However, as the results of organizational conflicts accumulated, the interaction between disparate knowledge becomes more likely to produce better knowledge than an existing one. This is called “constructive conflict” of an organization (Ellis et al., 2003; J. Hall & Williams, 1970; Maier & Hoffman, 1964).

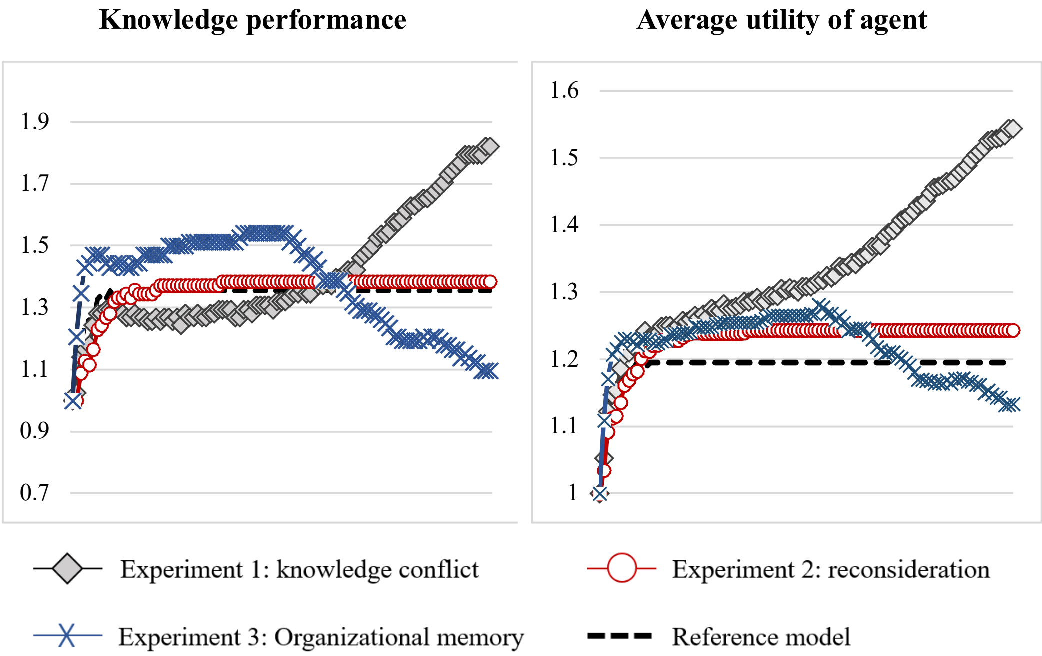


Figure 27. Organization performance and average utility from the experiments

The performance and utility of the organizational memory model (experiment 3) rapidly were rapidly improved in the early stage., Since then, they have been lower than those of the reference model. Insufficient organizational memory makes it difficult for organizational decision making difficult to fully benefit from valuable individual knowledge (M. Park, Lee, Lee, Jiayi, & Yu, 2013). However, organizational memory can have advantages in the decoupled organization that knowledge sharing occurs rarely (Wieck, 1976). Thus, constant interactions among the members is likely to constraint the benefits of it (Tufool & Gerge, 2013). That is why the effect of organizational memory on the performance and utility of organizations turns negatively as the knowledge interaction repeats.

The reconsideration of existing knowledge does not show a significant difference with the reference model. Evaluating alternatives is easy for the individual agent if the number of alternatives is small enough. The knowledge performance and average utility increased in the very early stage because the volume of alternatives was enough for an individual agent to handle. However, repeated knowledge interactions rapidly increased the number of alternatives and finally, this made people confused. In this perspective, previous studies argued that a strong leadership (Courtright, 1978; Montanari, 1986) or group cohesiveness (McCauley, 1989) is required to evaluate a large number of alternatives (Breitsohl et al., 2015). In addition, even though considerable alternatives are available, individual feedback too far from the organizational goals leads to the wrong belief that all alternatives were fully evaluated (Flippen, 1999).

From the three ABM simulations, this section provided some evidence about the influence of the single switching factor on the performance and average utility of an organization. However, the total effect of multiple factors is not the same with the sum of them in a complex adaptive system because interactions intervene on the evolution of a system (Kauffman, 1996). Thus, in the following section, combinations of switching factors are tested through the meta-frontier analysis which can compare the efficiency of heterogeneous strategies.

4.4 Finding the optimal strategy

4.4.1 Meta-frontier analysis

The meta-frontier analysis (MFA) is a methodology for comparing theoretical efficiency based on the production function of the industry. Since the components of these methodologies should be homogeneous (O'Donnell et al., 2008), it is hard to reflect the unique characteristics of heterogeneous subgroups (Battese, Prasada Rao, & O'Donnell, 2004; Coelli, Rao, O'Donnell, & Battese, 2005). Meta-frontier analysis was introduced for that reason. Meta-frontier analysis calculates the between-group efficiency based on the distance between meta-frontier and group-frontier (O'Donnell et al., 2008).

There are two kinds of way to estimate froniters of entities. First data enveloped analysis (DEA) is a methodology to measure the relative efficiency among the decision making units (DMU) based on Farrel (1957). After than, Charnes, Cooper, & Rhodes (1978) was considered as the beginning of DEA studies(J. Lee & Lee, 2012) (Lee et al., 2012). DEA has a advantage that no statistical assumption is required, so it can minimize the intervention of researchers' expectation. Naturally, it does not demand any pre-define production or cost functions of entities. The non-parametric property of DEA can be a methodological strength, but it can be a weakness of methodology at the same time. In other words, DEA can shows good performance in small sample data or when the researcher does not have any prior knowledge about statistical properties of data set, however DEA can not be statistically tested and less effective to indentify the source of efficiency.

Stochastic frontier analysis (SFA) is similar with DEA in terms of calculating the relative efficiency, it requires several strong assumptions. Aigner, Lovell, & Schmidt (1977) proposed that statistical turbulance should satisfy i.i.d (independently and identically distribution) condition and independece between statistical turbulance and total turbulance (S. S. Lee, 2011). This study uses the data set generated from virtual environment, so it rational the error terms satisfy i.i.d condition, and also we can secure large enough data as much as we need. In addition, SFA can statistically present the validity of estimation result, this study adopted SFA rather than DEA.

To utilize SFA for MFA, this study defiend the production fuction composed of inputs and output. So, first, inputs and output shoul be defined to develop a production function of an organization. There are many previous studies considering the organization as a system having inputs and outputs (e.g., Koohborfardhaghighi & Altmann, 2017; Koohborfardhaghighi, Romero, Maliphol, Liu, & Altmann, 2017; Macy & Willer, 2002; March, 1991; Nonaka et al., 2006). They emphasized that the organization is a social system for finding strategic decision-making (Koohborfardhaghighi et al., 2017) or knowledge (March, 1991; Nonaka et al., 2006). So, organizations can have various inputs and outputs based on their goals or roles. Despite this research model has a clear output which is the quality of knowledge, it is ambiguous define the specific inputs that have a concave relationship with the output. Previous studies have proposed a lot of factors for the organizational performance, for example the structure of social network (Ahuja & Carley, 1999; Reagans & McEvily, 2000), leadership(Cruz et al., 1999; McHugh et al., 2016) or even friendship (Grey, C., & Sturdy, 2007; Jehn, K. A., & Shah, 1997). However, on the perspective of the intersection between evolutionary computation and organizational learning, there are two fundamental and significant inputs: learning capability and diversity. Organizational learning model based on the genetic algorithm had defined 'learning' as imitating another's attribute (Levitt & March, 1988). According to this viewpoint, learning capability is a probability to imitate another's knowledge, so the higher learning capability refers to that more perfectly imitate another's knowledge. Naturally, high probability of imitation can accelerate the exploitation of an organization, consequently, the organization converge to the solution efficiently (Haupt & Haupt, 2006). That's why learning capability has been considered a crucial factor for organizational performance(Akhtar, Arif, Rubi, & Naveed, 2011; Ho, 2008; Lopez, Peón, & Ordás, 2005; Molina & Callahan, 2009; Posen et al., 2013; Yeung, Lai, & Yee, 2007). Also, diversity of organization is an important issue in its survavability. When the diversity is dropped below a thershold level, the organization will be stucked in to the local optimum (Chang et al., 2010), which is called 'genetic equilibrium'. For that, previous studies have focused on the maintenance of diversity in terms of adaptive (F.Herrera & M.Lozano, 1996), parametric (Eiben, Hinterding, & Michalewicz, 1999) and dynamic control (Huang, Chang, Hsieh, & Sandnes, 2011). As a result, this study assumes that learning capability and diversity are the main input of an organization as a system.

This study utilized a virtual dataset generated by the ABM simulation to identify the efficiency of each combination of switching factors. The ABM groups are classified into 8 groups each with a unique strategy. Details of the classifications are given in table 20 of the previous section.

Generally, the efficiency of each group is defined as a ratio between the input and output. The present study assumed learning capability and diversity as inputs of organizations and the organizational knowledge performance as an output. Appropriate level of learning capability (Levitt&March, 1988; March, 1991) and organizational diversity (Aggarwal & Woolley, 2013; Kozhevnikov, Evans, & Kosslyn, 2014) are known as important factors in determining the quality of organizational knowledge. However, excessive levels of learning capability and diversity can aggravate the quality of organizational knowledge (Levitt, B; March, 1988; Anita Williams Woolley et al., 2015). Thus, this study assumed a polynomial function to estimate the relationship between inputs and output.

$$perf_{i(j)} = \alpha_i + \beta_1 div_i + \beta_2 learn_i + \beta_3 div_i^2 + \beta_4 learn_i^2 + \beta_5 div_i learn_j + (V_i - U_i),$$

$$\text{where } V_i \sim N(0, \sigma_V^2), U_i \sim \left|N(0, \sigma_U^2)\right|$$

At every implementation of the ABM simulation, the learning capability and diversity of an organization were randomly assigned. The performance of organizations was measured by the quality of knowledge explained in the previous section. The stochastic frontiers of each group were estimated by FRONTIER 4.1 software and the meta-frontier for each estimated by MATLAB R2017a.

4.4.2 Comparison of strategies using switching factors

The efficiency of strategy used by each group are shown in Table 17. According to the estimation result, all the in-group efficiencies (TE) are high. This means that the agents of each model are fully utilizing the input resources to enhance their organizational knowledge performance. This also indicates that it is impossible to increase the efficiency of the organization with individual efforts alone.

Unlike the in-group efficiency, the between-group efficiency (TGR) towards the meta-frontier of each model shows a wider gap. Group 2, which has knowledge conflict and reconsideration, shows the highest between-group efficiency. Group 3 and group 5 show high efficiencies compared to the other models. These groups are also ranked highest in total efficiency (TE*). Therefore, we can say that the strategy of group 2 is the best and that of group 3 and 5 are also good enough to be considered as alternatives. Contrary to these superior groups, group 4 and group 7 show remarkably low efficiency.

Table 23. Estimation results for the SFA and MFA.

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	MFA
β_o	0.0002 (0.0076)	143.279 (7.0257)	-0.0011 (0.0012)	-0.0037 (0.0024)	-0.0014 (0.0041)	0.0004 (0.0041)	-0.0023 (0.0071)	0.0046 (0.0052)	1.5751
β_1	1.0098 (0.0176)	-1.1415 (0.1582)	1.0029 (0.0026)	1.0120 (0.0055)	1.0018 (0.0095)	0.0011 (0.0048)	1.0102 (0.0043)	0.9908 (0.0116)	-0.8463
β_2	-0.0107	13.0092	0.0005	-0.0031	0.0036	-0.0028	-0.0053	0.0095	1.4867

	(0.0107)	(10.353)	(0.0015)	(0.0031)	(0.0055)	(0.0028)	(0.0045)	(0.0067)	
β_3	-0.0104	0.0048	-0.0019	-0.0075	0.0003	-0.0011	-0.0076	0.0069	0.0076
	(0.0114)	(0.0010)	(0.0016)	(0.0035)	(0.0061)	(0.0031)	(0.0026)	(0.0075)	
β_4	0.0051	-10.535	-0.0004	0.0022	-0.0006	0.0011	0.0019	-0.0054	-3.2915
	(0.0062)	(6.8901)	(0.0009)	(0.0019)	(0.0035)	(0.0071)	(0.0002)	(0.0041)	
β_5	0.0058	-0.0083	-0.0001	0.0002	-0.0045	0.0016	0.0032	-0.0016	-0.2080
	(0.0075)	(0.0741)	(0.0011)	(0.0024)	(0.0041)	(0.0043)	(0.9908)	(0.0052)	
TE	**0.991**	**0.988**	**0.998**	**0.997**	**0.995**	**0.997**	**0.998**	**0.994**	1.0
TGR	**0.122**	**0.801**	**0.666**	**0.291**	**0.680**	**0.617**	**0.254**	**0.553**	1.0
TE*	**0.121**	**0.792**	**0.662**	**0.291**	**0.677**	**0.616**	**0.253**	**0.550**	1.0

※ TE: in-group efficiency, TGR: between-group efficiency, TE*: total efficiency = TE×TGR

In sum, the strategy of group 2 may be the optimum combination of switching factors. Combining the knowledge conflict and reconsiderations guarantees high efficiency in organizational knowledge creation. According to the results of group 7, the reconsideration of alternatives is not an effective strategy when it is adopted alone. Similarly, the choice of knowledge conflict becomes a defective strategy if organizational memory is being considered at the same time.

The primary goal of this analysis is to identify the optimum strategy by comparing combinations of switching factors for efficiency. The results of the meta-frontier analysis also provide some evidence about the strategies organizations should avoid. Initiating a new strategy is hard and risky in real world situations. However, stopping the incumbent strategy is relatively easier from the perspective of an organization. Thus, knowing what should not be done is sometimes more beneficial than knowing what to do.

The meta-frontier analysis produced two groups with strategies that should not be chosen.

First, reconsidering alternatives can be effective when a sufficient number of alternatives are available (Flippen, 1999). The sole use of reconsideration creates inefficiency in the creation of organizational knowledge. Second, the combination of knowledge conflict and organizational memory shows much lower efficiency than the other combinations. Previous studies argued that verifying the quality of knowledge is an important problem in the collective intelligence system (Choi, 2009) and that the validity of knowledge is strongly influenced by the evaluations of other people (A. J. Flanagin & Metzger, 2000; A. Flanagin & Metzger., 2008). Thus, it can be inferred that the inefficiency of group 4 is due to the lack of evaluation process or filtering towards the accumulated knowledge through knowledge conflict and memory.

4.5 Discussion

The ABM simulations were conducted in this study to suggest that “switching factors” stimulate the collective intelligence and found the optimum strategy by using meta-frontier analysis. To understand the creation of organizational knowledge and decision-making, our analyses presents valuable lessons on how to use the “switching factors” when expecting to transform groupthink into collective intelligence.

Despite contemporary organizations being complex and dynamically behaved (Coff, Coff, & Eastvold, 2006; Milosevic, Bass, & Combs, 2018; W. K. Smith & Lewis, 2011), problem solving the groupthink phenomenon has only stayed in Janis’ groupthink framework or its modified theories (Rajakumar, 2019). To create quality organizational knowledge, previous studies focused on how to remove groupthink based on the linear causalities (J. Esser, 1998; Rajakumar, 2019; Turner & Pratkanis, 1998c). However, just removing the groupthink phenomenon from an organization is not the best solution because it is an effective way to handle simple or routinized problems at low cost (I. L. Janis, 1982). In addition, knowledge bias which is recognized as a source of defective decision making also can be a natural product of the organizational consensus process (Solomon, 2006). That is why this study is interested in how to transform groupthink into collective intelligence.

This study emphasizes that groupthink can be converted to collective intelligence via switching factors including knowledge conflict, reconsideration, and organizational memory. Our findings indicate that an organization with groupthink can be moved closer to a collective intelligence organization by strategic use of the switching factors. The ABM simulation and meta-frontier analysis illustrated two facets of the switching factors.

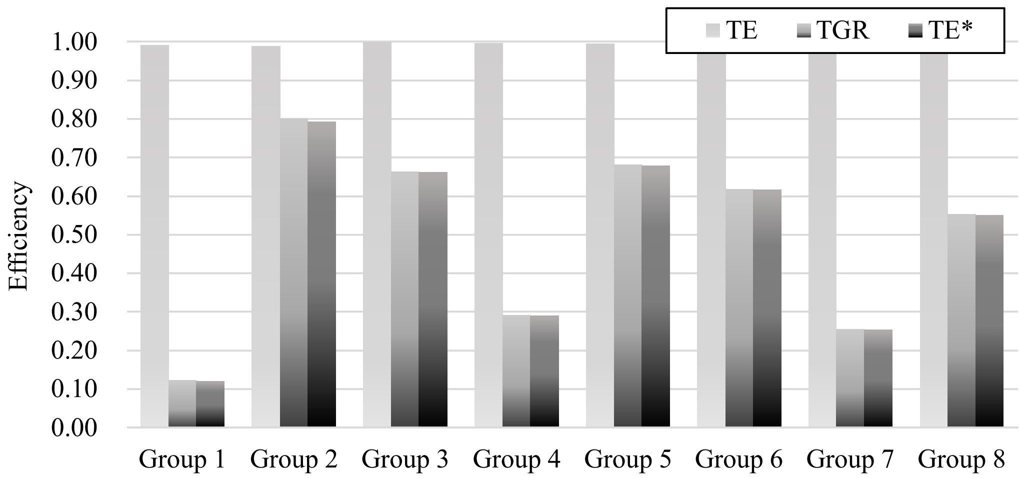
In the ABM simulation, the influence of each switching factors was investigated. Knowledge conflict clearly increases knowledge optimization performance but considerably biases the domain of individual knowledge at the same time. This finding supports the prior idea that knowledge conflict could be constructive when the task of the organization is complex. Conflicts between heterogeneous knowledge incur substantial costs when the organization has problems such as inconsistent and uncertain goals or defective communication (Chiocchio et al., 2011). If an organization is in that situation, knowledge conflict is likely to negatively work. On the other hand, an organization with a complex task requires sufficient knowledge conflicts (Jehn & Mannix, 2001) to not only expand the domain of knowledge but to also acquire new knowledge (Miranda & Saunders, 1995). More specifically, Jehn & Mannix (2001) explain that the need for knowledge conflict is increased when the organization has multiple perspectives.

Reconsideration of alternative knowledge is a factor that has been emphasized, especially in the prevention of groupthink phenomenon (Janis, 1982; Rajakumar, 2019; Riccobono et al., 2016; Turner & Pratkanis, 1998c). The results of ABM simulation suggest that while it is not effective on knowledge quality and individual utility, it does help preserve the diversity of individual knowledge. Previous studies pointed out that maintaining organizational diversity contributes to a reduction in the groupthink phenomenon (Fernandez, 2005; Solomon, 2006) or bringing collective intelligence (HWANG, Kim, & Lee, 2009; Loasby, 2002; Surowiecki, 2004).

Organizational memory has been highlighted in both studies on collective intelligence and knowledge management. Our findings presented a model where organizational memory creates an isolated knowledge area, which refers to the organizational knowledge memory. For creating collective intelligence, each organizational knowledge should be stored as a specialized form (Malone & Bernstein, 2015). In terms of knowledge quality and average utility, the effectiveness of organizational memory is rather skeptical. Over time, stored organizational knowledge loses efficacy and becomes an obstacle to change because individuals depend on retrieving knowledge rather than creating new knowledge (Starbuck & Hedberg, 1977; Walsh & Ungson, 1991). In the model with organizational memory, despite knowledge quality and utility raised until the middle stage, they decreased rapidly after the middle of the experiment and in the end, this model presented the lowest level in both knowledge quality and average utility. This finding gives evidence for the negative side of the organizational memory system.

In this study, we defined 8 strategic groups based on the combination of the switching factors. According to our findings, the strategy with knowledge conflict and reconsideration (group 2) represented the highest strategic efficiency. Knowledge conflict is based on heterogeneity, thus the agent who interact with other agents has two options. The first option is adhering to the incumbent knowledge. If all agents choose this option, knowledge conflict will be meaningless behavior. Conversely, when the agents change their knowledge based on the heterogeneous ones, there remains a problem. They should determine how much they will learn from the heterogeneous knowledge. Reconsideration of alternative knowledge gives some clues. The agents with reconsideration can determine the level of learning from the heterogeneous knowledge by comparing it with the alternatives they have. The combination of knowledge conflict and memory shows the lousiest efficiency with the exception of the groupthink model (Group 1). As mentioned above, people can choose whether they interact with the heterogeneous knowledge or not. Organizational memory provides a chance to interact with the knowledge that no one has currently. As a result, these organizational behaviors amplify the knowledge of mutual learning with a lack of adequate consideration or evaluation.

The results of the best and worst strategic group highlight the importance of "reconsideration." A point to remember is that, despite reconsideration, it is not an effective strategy utilized alone, but it is worth it when adopted with other switching factors. Knowledge conflict focuses on knowledge diversity (Miranda & Saunders, 1995) and organizational memory focuses on the volume of organizational knowledge (Kruse, 2003). Our findings show that just the volume and diversity of knowledge cannot guarantee the quality of organizational knowledge creation. To filter accumulated knowledge, reconsideration of existing alternatives is an imperative procedure of the organizational knowledge creation process. Hence, this study provides support to accumulated knowledge and its appropriate evaluation are able to result in organizational diversity and decentralization which are essential factors for collective intelligence (Solomon, 2006).



Group1	**Group2**	**Group3**	**Group4**	**Group5**	**Group6**	**Group7**	**Group8**
Reference (groupthink)	Conflict Reconsider	Reconsider Memory	Conflict Memory	Conflict Reconsider Memory	Conflict	Reconsider	Memory

Figure 28. Comparison of the strategy of each group

4.6 Conclusion and limitations

Since an organization aims to effectively solve enormously complex problems, internal organizational interactions have been emphasized over individual capacity (Chiocchio et al., 2011). Organizational knowledge is created by various organizational behaviors (Alavi & Leidner, 2001; Ikujiro Nonaka & Konno, 1998) and knowledge bias occurs during this process. If there is not appropriate management, knowledge bias can lead organizations to an extreme tendency called groupthink. Previous studies suggest diverse ideas to prevent organizational failure and promote collective intelligence (Rajakumar, 2019). In particular, the development of information technology has made collective intelligence a prominent capacity of organizations (Alag, 2008; Lykourentzou et al., 2011; Musser & O'reilly, 2007). Despite the technological foundation, there have been few discussions about strategical solutions of groupthink and collective intelligence.

This study provides several lessons to not only the knowledge management area but also innovation theory. First, the reconsideration of alternatives is an essential process to fully exploit the existing organizational knowledge. In particular, the combination of knowledge conflict and reconsideration may be the best way for stimulating collective intelligence in groupthink situation. Conversely, simultaneous use of knowledge conflict and organizational memory should be avoided for effective use of collective intelligence. Also, in terms of innovation theory, this result can provide an evidence for strategies to solve problems (Hargadon, 2002) and to increase the organizational performance(K. Kim, Altmann, & Kim, 2019).

If the ABM simulation methodology is designed based on empirical data, that simulation has an advantage in its accuracy. However, this study did not calibrate the ABM due to the lack of real data relevant to our research topic. Thus, the calibration based on real data is expected to enhance the reality of the simulation model. Also, the extension of parameters and functions are needed to make the ABM more elaborate.

Chapter 5. Effect of emerging technologies on the organizational knowledge creation: the use of big data analytics and online platforms

5.1 Introduction

Technologies have changed not only our daily life but also organizational capability, behavior and system fundamentally. Especially, development of information and communication technology (ICT) dramatically has increased both the connectivity of organizations and the speed of information processing, and ultimately provide an environment for open innovation so that the knowledge permeates into the organization (K. Kim & Altmann, 2019). So, reliance on ICT is generally unavoidable (Will, 1991). With the beginning of the fourth industrial revolution, the conjecture that ICT will effectively solve our social problems has become social confidence. Response to those expectations, the benefits from ICT development have contributed to resolving the crucial social dilemma such as asymmetry of information, optimal allocation of limited resources, effective collaboration and accumulation of knowledge (Alavi & Leidner, 2016; Faraj et al., 2011; Täuscher, 2017).

Consequently, the use of technology has become a critical factor and basis of knowledge creation and management. The advances in ICT facilitate cooperation of organization even though they are geographically dispersed. ICT-based knowledge management system make people going beyond the socio-cultural obstacles which inhibit knowledge interactions, such as politics, trust, authority, hierarchy or concerns about personal relationships (Omotayo, 2015; Sun & Scott, 2005). In addition, emerging technologies transform the traditional functions into new area. For example, the customized recommendation system in AMAZON is being provided by artificial intelligence algorithms rather than human intuition or deduction. Big data and AI technology actively intervene in the area considered as the unique ability of humans such as decision-making process, knowledge recombination and finding patterns (Grossman & Siegel, 2014). In addition, according to the previous studies, participation in online platforms has been identified as a catalyst of knowledge collaboration (Faraj et al., 2011) and collective intelligence (Luo et al., 2009). So, this study focuses on BDA and online platform in terms of organizational knowledge creation.

(Problem description)

Contrary to the positive view toward the technology in the organizational knowledge creation, several studies proposed a possibility of negative effect of the use of technology on the organization. In this context, Nonaka (2000) argued that changes of technology environment can induce rapid decline of organizational performance. Also, Mohamed et al. (2009) raised a possibility the use of technology can give the negative effect on sustainable development of an organization. Especially, Chou and He (2004) emphasized that the use of technology bring to whether negative or positive effect because organizational performance is sensitive to it. However, it is hard to find the studies dealing with both side of technology usage in knowledge management area. Therefore, considering positive and negative effect of the use of technology simultaneously is necessary work for providing a foundation to identify the effective way to use technology in the organization.

From the perspective of the organization, the advancement of technology improves the value of the organization and its members through establishing a new paradigm of knowledge creation (Täuscher, 2017), and furthermore, reinforce the process of social knowledge production (Hwang et al., 2009). However, previous literature have several limitations. First, as metioned before, they have focused on the advantage of using technology in terms of knowledge management (e.g., Devaraj and Kohli 2003; Kelley 1994; Liao 2003; Lichtenthaler and Lichtenthaler 2009; Pentland 1995; Alavi and Leidner 2016). Second, on the perspective of knowledge management, technologies used in the organization were limited as information systems (IS) supporting organizational operation (L. S. Kim, 2015) and BDA (e.g., Akter, 2016; Mikalef et al., 2017; Mikalef, Pappas, Krogstie, & Giannakos, 2018; S. K. Singh & Del Giudice, 2019). Despite the benefits of online platforms are being increased (Malone & Bernstein, 2015; Faraj et al., 2011), previous studies focused on only BDA, and have relatively overlooked the importance of online platforms.

In addition, since the major interest of knowledge management area is maximizing organizational performance (Ikujiro Nonaka & Toyama, 2003), the organizational outcomes got more attention to measure the effect of the use technology through traditional indices such as financial performance (Jungho Lee, Kim, & Kim, 2006; Leidner & Kayworth, 2006). However, in modern organizations, knowledge activity can be more suitable measurement the organizaitonal performance (Davenport & Prusak, 1998). According to the previous studies, capability to create knolwedge is considered one of the most improtant source of organizational competitive advantage (e.g., Nonaka, 1990, 1991, 1994; Nelson, 1991; Leonard-Barton, 1992, 1995; Quinn, 1992; Drucker, 1993; Nonaka & Takeuchi, 1995; Grant, 1996; Sveiby, 1997). Smith et al. (2005) found out that organizational knowledge creation capability can enhance the organizational performance. In this context, Su et al. (2016) provide a supportive evidence the positive impact. However, most studies have considered the relationship between knowledge generation capabilities and organizational performance, and have overlooked the relationship between the use of technology and the capability of organizational knowledge creation.

Lastly, task complexity is one of the important context of organization in terms of groupthink and collective intelligence. In the groupthink studies, complex task is a source of groupthink by decreasing the self-efficacy of organization (Baron, 2005). Also, high complexity of task can increase the uncertainty of decision makings (McCauley, 1998) and exagerate the reliability of them (Wildavsky, 1998). In other words, groupthink studies considers the task complexity as a potential source of groupthink and failure of decision-making. Convserely, task complexity is a positive context for stimulating collective intelligence. From the perspective of collective intelligence, it is easy to occur when the task is complex requiring many resources, for example, crowd-sourcing (Bigham et al., 2015). Even though the task does not require many resources, it is better to handle the interdependent or highly connected tasks through collective intelligence (Argote, 1982; Malone & Bernstein, 2015). Especially, McHugh et al. (2016) found out that the complexity of task mediates the level of collective intelligence and the quality of outcomes.

Therefore, this study aims to figure out the two-sided effect of emerging technologies, which are big data analytics (BDA) and online platform, on the organizational knowledge creation. In addition, when this study estimates the effect of technologies, the property of task which is 'complexity' is considered as a mediator. Based on this research objective, three research questions are developed: (1) Is the use of BDA or online platform can enhance the knowledge creation capability? (2) Are these effects invariant with the level of task complexity?. This study adopted two statistical model to answer these questions. Based on this research questions, this study establishes four hypotheses. To answer to the first question, two hypotheses are developed as below.

Hypothesis 1. The relationship between the use of BDA and the organizational knowledge capability follows an inverted U-shape.

Hypothesis 2. The relationship between the use of online platform and the organizational knowledge capability follows an inverted U-shape.

Also, for the second question of the mediating effect of task complexity, there are two hypotheses.

Hypothesis 3-1. The high complexity of task intensifies the effect of the use of BDA on the capability of organizational knowledge creation.

Hypothesis 3-2. The high complexity of task intensifies the effect of the use of online platform on the capability of organizational knowledge creation.

In order to examine four hypotheses, this study identifies the effect of the use of BDA and online platform through two regression models. Linear model and polynomial model are adopted and compare those estimation results to show clearly the relatioships between the use of technology and knowledge creation capability. The dataset for estimation was collected by survey from 350 respondents in Korea. Based on the level of task complexity that respodents answered, sample is divided into two groups: high task complexity and low task complexity. The results of linear regression model present that the use of BDA significantly increase the level of knowledge creation capability, but the effect of online platform usage is uncertain. Polynomial regression model shows more elaborate result than those of linear model. The result points out that the use of BDA may ineffective under the excessive level but ineffectiveness of the use of online platform is assured. However, those results are only valid if the task complexity is high. When the task complexity becomes lower, the use of both technology enhances the knowledge creation capability regardless of their degree.

Based on these several results, this study is able to provide two implications to knowledge management area. First, this study provide an evidence for guideline for the use of technology by their task types. In term of organization, the importance of this guideline will be larger than before because of the development and percolation of technology. Second, the result of this study pointed out that these guidelines should be modified by the types of task. Especially, this study shows the task complexity can change the relationship between the use of technology and knowledge creation capability.

The outline of this study consist of three sections. Section 5.2 describes the detail explanation of previous studies supporting our idea. In section 5.3, the introduction of research model, dataset and the result of estimations. Lastly, section 5.4 delivers discussions and implications of this study derived from the result of the analyses in the previous section.

5.2 Technology and organizational knowledge creation

Knowledge is created in various ways. Organizational knowledge can be generated by individual inspiration, routine or technical systems. This study focuses on the role of technologies in the organizational knowledge creation process.

This study has one dependent variable and two independent variables and one meditating variable. The dependent variable of this study is the organizational knowledge creation capability which reflects the relative level of collective intelligence and groupthink. The independent variables are defined as the use of BDA technology and online platform in context of their tasks. Task complexity is a mediating variable manipulating the relationships between the dependent variable and independent variable or their intensity. The detail concept and explanation will be presented in following sections.

Big data and artificial intelligence technology opened a new method of organizational knowledge creation. Since these technologies have changed organizational behaviors (Malone & Bernstein, 2015), adopting new technologies requests considerable validation of their ramifications toward the entire organization. In this study, to investigate the expected result of the use of BDA and online platforms, eight hypotheses were developed and examined.

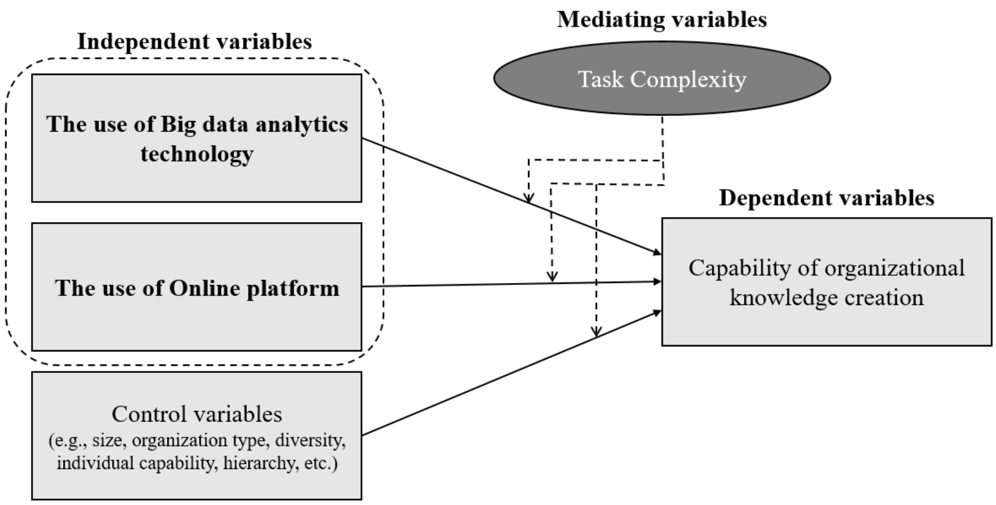


Figure 29. Brief description of research model

5.2.1 Organizational knowledge creation

The depdent variable of this study is the capability of organizational knowledge creation. It is hard to measure the quality of knowledge directly because knowledge is a combination of qualitative and quantitative aspect. Thus, previous studies have considered alternative ways to measure organizational knowledge through various proxies. In general, the number of patent and academic paper have been utilized to quantify the organizational knowledge. However, the patent can reflect the knowledge that the outcomes of the research and development process, and the academic paper have a limitation that it is likely to be created by certain types of organizations such as schools or research institutes.

Thus this study measures the quality of knowledge from the perspective of organizational capability through two conventional concepts: groupthink and collective intelligence. The level of collective intelligence measured by the method used in Bates and Gupta (2017b) and Woolley et al. (2010), and the level of groupthink complies the measurement of Lee et al. (2016). To calculate the capability of organizational knowledge creation (CAP_i), the ratio between the score of collective intelligence and that of groupthink is used. This study defines the knowledge creation capability as follow:

$$CAP_i = \frac{Score\ \ of\ \ collective\ \ intelligence_i}{Score\ \ of\ \ groupthink_i}$$

5.2.2 Big data analytics

Big data analytics (BDA) is where advanced analytic technique handling with big data sets and its property is determined by three Vs including volume, velocity and variety (Russom, 2011). On the perspective of knowledge management, BDA takes an important role in a business framework for an organization. Grossman & Siegel (2014) specifically explained organizational analytics though GSPG framework consisting of culture, staff and process. This study only considered the aspect of process in GSPG.

Table 24. GSPG framework for organization analytics

Factor	Department / Unit level	Organizational level
Culture	Are big data and analytics viewed as an organizational function and is there a big data/analytics department or unit to support this function?	Are big data and analytics integrated into corporate strategy? Is there a senior leader advocating for big data and analytics? If not, put a senior leader in charge of big data and analytics with this charge. Is data (both internal and external) that can provide value being used?
Staff	Does the analytics department have the right people with the right degree of analytic specialization, It knowledge, and business knowledge?	Are there analytic team members in the right departments within the organization and is there a critical mass of analytic talent? If not, rebalance the analytic staff or change the centralization/decentralization of the analytics staff as required.
Process	Does the analytic department have analytic processes in place to build analytic models, deploy analytic models, and measure their business impact?	Does the organization have the analytic processes in place to select analytic opportunities, provide data to the data scientists, build analytic models, deploy analytic models, and measure the business value generated? Is there an analytic governance structure in place to support and to coordinate the correct

	analytic processes?

(Source: Grossman & Siegel, 2014)

BDA technology plays a critical role in the process of knowledge management(Pauleen & Wang, 2017). These technologies have been known as that support human decision making and knowledge creation (Malone & Bernstein, 2015). Especially, BDA has advantages in some tasks which are beyond human capability, such as group classification, coexistence of characterization and diversification (De Vincenzo et al., 2018) and digital archive (Bieber et al., 2002). Thanks to the benefit of them, the use of BDA ultimately is able to improve the level of organizational capabilities including efficiency, effectiveness, competitiveness, and creativity (Kohn & Hüsig, 2006).

However, excessive use of big data and AI is able to produce ineffective outcomes. When an organization is under the decision making or knowledge creation process, a certain level of human capability should be required, for example, human insight, vision, and organizational culture (Mcafese & Brynjolfsson, 2012). In addition, BDA technology should involve the investigations by human (Kornienko et al., 2015), such as the verification of data consistency and adequacy of sources (Janssen et al., 2017; Kadadi et al., 2014). Therefore, there should be a certain level of balance between the use of BDA and human intervention.

Hypothesis 1. The relationship between the use of *BDA* and the organizational knowledge capability follows an inverted U-shape.

5.2.3 Online platform

According to the previous studies, online platforms are distiguished by four types in terms of the role of users (Kwon & Wen, 2010). First type of platform refers to an web-based platform-as-a-service (PaaS) that provide applications for performing, stroing and managing the users' works (Lawton, 2008) to create and dstiribute values (Haile & Altmann, 2016). In other words, this is the buisiness model based on online platforms. Web2.0 services such as Google, Yahoo, Amazons (K. Kim, Altmann, & Hwang, 2010) are included in this type of online platform.

The second type of online platform shows some different properties in terms of the role of users. This kind of online platform strongly requires the participant of users, which is called collective intelligence tool such as Wiki-based platforms and open communities (Chu, Siu, Liang, Capio, & Wu, 2013; Naismith, Lee, & Pilkington, 2011). Although, PaaS also need the user's active participation, but it is just an additional element, and the core competitiveness lines in the capability of the service provider such as usefulness (Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, 2004), price (Razavi & Israeli, 2019), creadibility (Thomas, Wirtz, & Weyerer, 2019), privacy (Anic, Škare, & Kursan Milaković, 2019) and etc. Contrary to that, collaborative online platforms emphasize connectivity (Curran, 2002), motivation (Bigham et al., 2015). Not only Wiki-based services, the other collaborative services such as Kickstarter (Kuppuswamy & Bayus, 2013).

The third online platform is a relationship-oriented platform such as SNS, which is defined as an web-based service enabling online relationships through collecting and sharing information with unspecific users (Kwon & Wen, 2010).

The last form of online platform is collective emotion tools. This type of platform is almost similar to the relationsguo-oriented platform, but this more focuses on the expression and sharing knowledge collectively rather than individual interaction. This study only considered task or functional oriented platforms because this study fosues on the capability of organizational knowledge creation rather than building networks or personal relationships.

Knowledge ecosystem is a complex system composed of various actors and their interactions. The advances of ICT have spread the authorities about knowledge while connecting individual knowledge. From the collective intelligence view, these characteristics of online space changed the mechanism of knowledge creation (Kim & Hong, 2011). Especially, emergence of Web2.0 dramatically increased the openess of network and it led to collective intelligence through exchange of resources such as knowledge and information (K. Kim et al., 2010). In terms of that, online platforms have played an important role in integrating dispersed individual knowledge to transform into a huge brain (Fredberg, Elmquist, & Ollila, 2005). As a result, collaborations on the online platforms unprecedentedly enhanced not only organizational knowledge capacity but also individual capabilities (Lykourentzou et al., 2011; Sproull & Arriaga., 2007), and now, the online platform is perceived as a critical channel of utilizing collective intelligence (Alag, 2008; Musser & O'reilly, 2007).

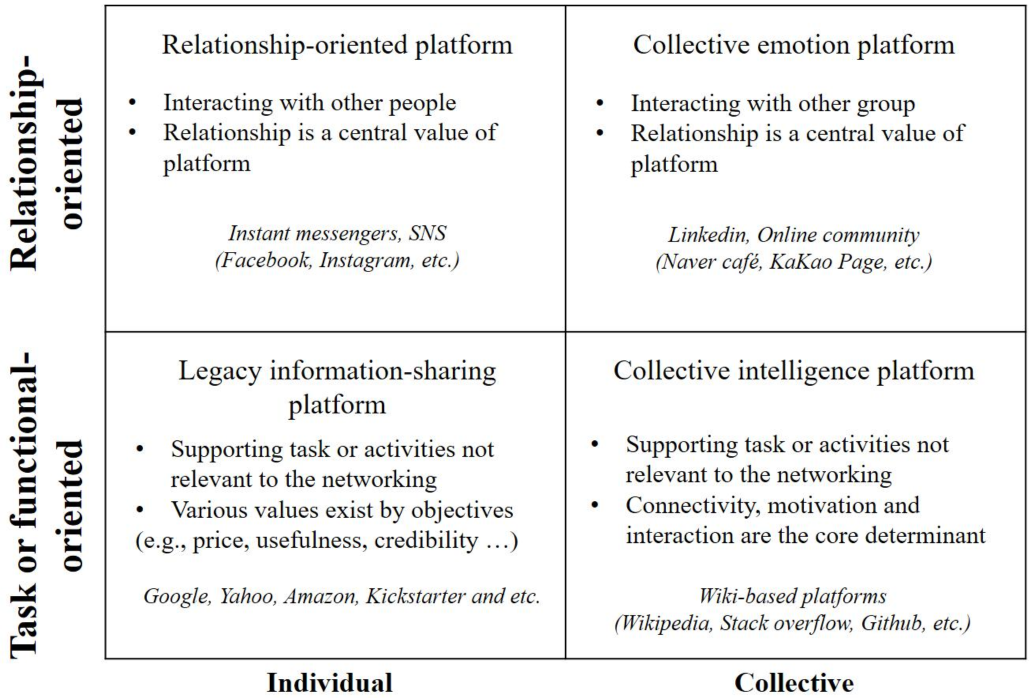


Figure 30. Categories of online platforms in terms of the role of users

On the contrary to that, previous studies have suggested the potential side effects of the use of online platforms. Størseth (2018) and Breitsohl et al. (2015) argued that groupthink in an online platform can be more intensified than the offline organization. In Størseth (2018), the reason of groupthink comes from compliance developed by exaggerated social sensitivity called ‘cyber conformity’. Breitsohl et al. (2015) revisited Janis groupthink model to find out the significant factors of online groupthink phenomenon, and argued that group insulation and stress can increase the tendency of groupthink in financial online platform. In addition, excessive use of the online platform can induce some side effects such as the moral hazard (Massari et al., 2019) and dogmatic behavior by overindulgence

(Faraj et al., 2011). In addition, Dhir, Yossatorn, Kaur, and Chen (2018) argued that participating in online platform can lead to ‘media fatigue’ which deteriorate the human capabilities of both physical and mental aspect.

Hypothesis 2. The relationship between the use of *online platform* and the organizational knowledge capability follows an inverted U-shape.

5.2.4 Task complexity

Knowledge collaboration is very dependent on the type of task (Engel et al., 2014), so the type of task is an important aspect to determine the way to create organizational solutions. Complex task requires higher level of cooperation. Since high complexity in the task can increase uncertainty of organizational outcomes (Turner & Pratkanis, 1998c), it is more effective to use an unstructuarized method for creating solutions (Argote, 1982). McHugh et al. (2016) examined the mediating effect of task complexity on the relationship between collective intelligence and organizational performance. In that study, it is figured out that the high complexity of task increases the influence of collective intelligence on the organizational performance. Similar to McHugh’s study, Langfred and Shanley (1997) argued that complex interdependency of task can determine the effect of social cohesiveness on the organizational performance. Also, the members of an organization need to know the way how to cooperate with when the task and environment is complex (Chiocchio, 2007; Chiocchio et al., 2011). To sum up, the studies above imply that the way of creating new knowledge depends on the complexity of task.

Hypothesis 3-1. The high complexity of task intensifies the effect of the use of *BDA* on the capability of organizational knowledge creation.

Hypothesis 3-2. The high complexity of task intensifies the effect of the use of *online platform* on the capability of organizational knowledge creation.

5.3 The effect of technology usage

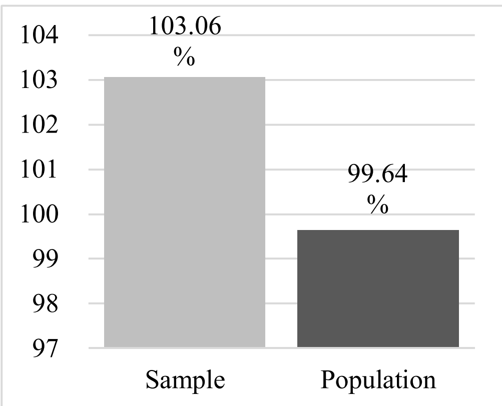
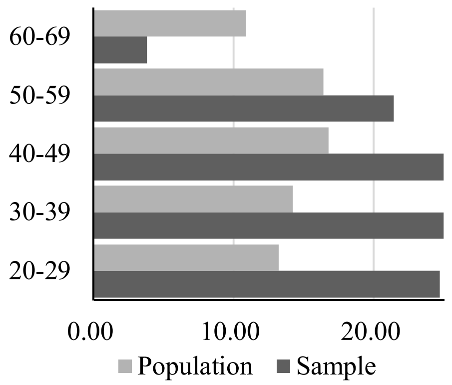
5.3.1 Data

This study conducted an online survey on 300 Korean people during 5 days from the 1st of November to the 5th of November in 2019. The survy is carried out by Macromil Embrain which is specialized in the online survey. At the pre-survey stage, 1,168 repondents participate in the online survey, however, I excluded observations which is not suitable for this study. First, if the respondent does not belong to the organization or belong to the organization which is smaller than 10 members. In too small organizaiton, it is hard to observe the organizational knowledge collaborations. Second, even if an organization has a size of 10 or more members, educational organizations have not been included in because those kind of organization aims to teaching and learn rather than create new knowledge via organizational collaborations.

This study used a data set containing 254 observations that the extremely biased or consistent respondent are excluded. This data can be divided into the high task complexity group (nhigh=117) and the low task complexity group (nlow=126) based on the average value of task complexity of the sample (average task complexity = 2.15, std. dev = 1.13).

Individual demographic characteristics are shown in the table 19. The age was evenly distributed among those from the 20s to 50s, and 51% of sample is female and 49% is male. The 50.51% of respondents belong to the administration and financial division, 13.27% is in R&D. Most of respondents are full-time employees (76.02%) and 12.24% of respondents are part-time employees. The size of organization shows quite equal distribution from 10 to 500. The organizations that is between 150 and 500 were largest (38.26%), and the organization with under 50 member (34.69%) follows that. Education level of participants were concentrated on the college level (77.04%). Although this statistical characteristics of survey data are not exact to same to the population, it may be more suitable for the population that just involves the economically active persons.

Table 25. Descriptive statistics of survey data

Gender ratio	Age
 (Source: Statistics Korea, 2018)	 (Source: Ministry of Public Administration and Security, 2018, Total Survey of Population and Housing in 2018)
Task	Position

Task	%	Position	%
Administration and finance	50.51	Part time	12.24
R&D	13.27	Full time	76.02
Marketing	4.59	Manager	6.63
Distribution	5.61	Board	2.81
Etc.	26.02	Etc.	2.30

Organization size		Education level	
Size	%	Education	%
Under 10	0	High school	14.28
10~49	34.69	College	77.04
50~149	23.97	Master	6.63
150~500	38.26	Ph.D.	2.04
Over 500	3.06		

5.3.2 Measurement

In order to measure the capability to create organizational knowledge, collective intelligence and groupthink should be measured. Groupthink consists of three subcomponents of group cohesion, structural fault and provocative context (Janis, 1982). Since Janis's concepts of groupthink were criticized by its ambiguity and unmeasureability (Longley, J., & Pruitt, 1980; Steiner, 1982), this study measured groutphink through both the symptoms of grouthink proposed in Leana (1985) and the basic concepts in Janis(1982). After collective intelligence had been figured out as an single factor which is independent to the individual capabilties (Woolley et al., 2010), various measurement were tried to identify collective intelligence accurately. Among them, ‘Theory of Mind’ (ToM, IA, 2012) ability was raised as a potential measurement of collective intelligence because of its correlation with the capability of organizational knowledge creation (Engel et al., 2014). Therefore, this study combined the concept of social sensitivity (Woolley et al., 2010) and ToM (IA, 2012) to measure the level of collective intelligence.

Measuring the use of technologies was achieved by the combination of several items. This study follows the measurement of ease of use and usefulness in technology acceptance model (F. D. Davis, Bagozzi, & Warshaw, 1989), and the trust and perceived risk are considered as items for measuring the use of technologies (Pavlou, 2003).

The use of technology had been measure by perceived usefulness and ease of use which are accepted in the diffusion theory of Rogers (1983). Perceived usefulness and ease of use affect to not only the use of technology but also the positive attitude toward that technology (Zhou, 2008). First, the perceived usefulness is defined as a level of belief that the use of a technology increases the individual performance (Davis, 1989). Since the technology covers both BDA and online platform, it is rational to adopt it as a measurement of technology usage. Second, the perceived ease of use refers to the level of belief that the technology can be utilized without additional effort (Davis, 1989). The domain of ease of use covers from the actual usage to get some requisite abilities. This study borrowed the items of Davis (1989) and modified it suit for the context of BDA and online platform technologies.

Also, perceived risk relfects the uncertain effect of technology. This uncertainty become higher when the technology is newer (Cha et al., 2019). So, perceived risk is defined as an uncertainty of technology usage (Im, Kim, & Han, 2008), in other words, it refers to the differences between the expectation and the actual result of technology usage (Sweeney, Soutar, & Johnson, 1999). We used the questions of Im et al. (2008) to meausre the percieved risk of technology usage.

Trust toward the technology can be an important determinant of the use of technology (Pavlou, 2003). Trust is defined as an expectation that another party behave based on the expectation that performs particular actions (Allen & Wilson, 2003). Different to the traditional offline trust, online trust is created by interactions among people (Bart, Shankar, Sultan, & Urban, 2005). Since, trust has been defined, examined and operationalized in many ways (McCloskey, 2011), this study borrowed the concept of trust that fulfil the users' expectation (Gefen, 2000; Warkentin, Gefen, Pavlou, & Rose, 2002).

In addition, the size of organization (Jang & Park, 2015), gender ratio (Woolley et al., 2010; Anita Williams Woolley et al., 2015), type of organization (Golkar, 2013; Hällgren, 2010) , individual capability (Bates & Gupta, 2017b) and the organizational equality (Woolley et al., 2010) are also adopted as the control variable of the capability of organizational knowledge creation. This measurements were collected in the pre-survey stage.

The organizational task complexity is introduced as a mediating variable between the use of technology and organizational knowledge creation capability. Complexity of task is defined as am average score of three aspects: interdepedency, multi-disciplinary and time consuming (Casey-Campbell & Martens, 2009; Ellis et al., 2003; Malone & Bernstein, 2015). Interdepdence of task is the level of reliance on another to achieve the tasks effectively in their given domains (Georgopoulos, 1986). Task interdepdence affect on the organizational performance (Shea & Guzzo, 1987) and the mechanism of interaction within the organization (Gersick, 1989). In this study, the interdependence of task was measure via the item developed by Van der Vegt, Emans, and Van de Vliert (2001).

The interdisciplinary task is distinguished into two perspectives. They are the organizational structural perspective and practice perspective. The organizational structure perspective emphasizes the specialized ability of each division, so the interdependence among the specialist is an important issue (Ben-menahem, M & Schneider, 2016). Conversely, the practice perspective points out the collaboration through the informal behaviors (Okhuysen & Bechky, 2009). This study follows the first perspective which is organizational strucutrue view because the informal collaboration is hard to quantify and it depends on the personality rather than the organizaitonal characteristics (Ben-menahem, M & Schneider, 2016). To measure the interdisciplinary, we developed the item based on the concept of the organizatinl structure perspective. The mean, standard deviation, skewness and kurtosis of each measurement is in table 26 shown below. In order to the confirm the validity of dataset, principal component analysis using R. The result shows that all measurements can explains 67% of variances appropriately. The detail result of is in appendix 12.

Table 26. Summary statistics of questionnaire

Item	Content	Mean	Std. dev	Skew	Kurtosis
Groupthink symptom	Overestimation	3.384	0.8	-0.38	-0.07
	(Chapman, 2006; Hart, 1991)	3.164	0.88	-0.32	-0.02
	Closed mindedness	2.696	0.93	0.33	-0.39
	(Janis, 1982; Ferraris and Varveth, 2003)	3.116	1.06	0.1	-0.63
	Uniformity pressure	3.152	0.91	0.19	-0.49
	(Janis, 1982l Hassan and Golkar, 2013)	2.576	0.84	-0.45	-0.03
ToM score	Empathic ability (IA, 2012)	2.844	0.99	0.16	-0.55
	Emotional sensitivity (IA, 2012)	2.624	0.92	0.4	-0.45
	Social sensitivity 1 (Woolley et al., 2010)	3.148	0.96	0.31	-0.6
	Social sensitivity 2 (Woolley et al., 2010)	3.252	0.8	-0.5	0.06
The use of BDA	Ease of use (Davis, 1989)	2.964	0.84	-0.21	-0.1
	Utility (Davis, 1989)	2.552	0.83	-0.14	-0.46

	Trust (Gefen, 2000; Warkentin et al., 2002)	2.632	0.81	0.44	-0.19
	Priority	2.636	0.85	0.3	-0.49
	Perceived risk (Im et al., 2008)	2.752	0.85	0.33	0.05
The use of Online platform	Ease of use (Davis, 1989)	2.632	0.85	0.18	-0.35
	Utility (Davis, 1989)	2.828	0.86	0.36	-0.39
	Trust (Gefen, 2000; Warkentin et al., 2002)	2.816	0.86	0.34	-0.2
	Priority	2.732	0.87	0.36	-0.4
	Perceived risk (Im et al., 2008)	2.844	0.85	0.06	-0.52
Organizational diversity	Gender (Woolley et al., 2010)	2.955	1.51	0.33	-1.02
	Background knowledge	3.355	0.86	-0.53	0.16
Organizational equality	Opportunity (Woolley et al., 2010)	3.325	0.90	-0.43	-0.41
	Importance (Woolley et al., 2010)	3.298	0.90	-0.39	-0.41
	Atmosphere (Woolley et al., 2010)	3.096	0.91	-0.16	-0.28
Organization size	Number of member	3.084	0.94	0.034	-1.49
Organization type	Type of task that the respondent is engaged in	-	-	-	-
Individual capability	Level of background knowledge (Woolley et al., 2010, Bates & Gupta, 2017b)	2.744	0.87	0.09	-0.77

	Task relativeness (Woolley et al., 2010, Bates & Gupta, 2017b)	3.116	0.83	0.34	-0.37
	Task understanding (Woolley et al., 2010, Bates & Gupta, 2017b)	3.088	0.72	0.09	0.24
Task Complexity	Task interdependency (Van der Vegt et al., 2001)	3.292	0.74	-0.26	0.42
	Multi-disciplinary (Ben-menahem, M & Schneider, 2016)	3.092	0.68	-0.21	-0.12
	Time consuming	1.996	0.71	0	-0.37

5.3.3 Regression model

This study applied two regression model in order to test the hypotheses. Two regression model, the linear regression model including only 1st order terms and the polynomial model including both 1st and 2nd order terms of the technology usage. Each model was classified into three sub-models as BDA model only involving the use of BDA, online platform model which includes the use of online platform and the unified model including both the use of BDA and online platform. The linear models which have the 1st order terms of the technology usage and control variables are shown below.

BDA: $CAP = \alpha + \beta_1 Use_{BDA} + \beta_2 X_{cont}$

Online platform: $CAP = \alpha + \beta_1 Use_{OP} + \beta_2 X_{cont}$

Unified model: $CAP = \alpha + \beta_1 Use_{BDA} + \beta_2 Use_{OP} + \beta_3 X_{cont}$

Polynomial regression model has been widely used in the organization researches. The use of polynomial model has an advantage where the components are measured differently or the model includes high-order terms (Edwards and Parry 1993; Yang et al. 2008). Especially, Yang et al. (2008) discovered that polynomial regression model is more effective than the other models for understanding the person-environment (P-E) problem or the human-related phenomena. The polynomial regression model including both 1st and 2nd order terms of the use of technologies and 1st order terms of control variables are shows below. Since this study didn't assume the moderate effect between the use of technology (Yang et al., 2008), the intersection terms were omitted.

BDA: $CAP = \alpha + \beta_1 Use_{BDA} + \beta_2 Use_{BDA}^2 + \beta_3 X_{cont}$

Online platform: $CAP = \alpha + \beta_1 Use_{OP} + \beta_2 Use_{OP}^2 + \beta_3 X_{cont}$

Unified model: $\mathrm{CAP} = \alpha + \beta_1 \mathrm{Use_{BDA}} + \beta_2 \mathrm{Use_{OP}} + \beta_3 \mathrm{Use_{BDA}^2} + \beta_4 \mathrm{Use_{OP}^2} + \beta_5 \mathrm{X_{cont}}$

5.3.4 Result: the effect of the use of technology

This study used R software to conduct the statistical estimation. Analyses were conducted by 243 observations. Table 19 and table 20 report which regression model is better to capture the effect of the technology usage on organizational knowledge creation capability. The use of BDA (Use_{BDA}) significantly affects to knowledge creation capability in linear regression model, and also in polynomial regression model. In the polynomial model, both 1st (ceff=0.32777, p-value=5.37e-7) and 2nd (coeff = -0.09412, p-value=0.00884) order terms of the use of BDA are statistically significant. The minus sign of 2nd order term refers to that the relationship between the BDA usage and the capability of organizational knowledge creation is concave. These results are similarly shown in the unified regression model too. These results support hypothesis 1 empirically.

The use of online platform (Use_{OP}) is not significant factor in both regression models. Both 1st and 2nd order terms of the use of online platform are found that they are not significant even in the polynomial regression model. Only in the unified linear regression model, the use of online platform significanlty influence on the capability of organizational knowledge creation. As a result, online platform usage does not enhance the knowledge creation capability. Thus, hypothesis 2 is able to be rejected.

Table 31 reports the result of mediating effects of task complexity. The 'high complexity' column refers to the result of a group which is recognizing that their task is relatively complex. According to this result, the inversed U relationship between the use of BDA and organizational knowledge creation capability is still maintained regardless of its task complexity. However, a different result is derived in the low complex task group. The 'low complexity' column in table 31 shows that both the use of BDA and online platform give positive effects to the capability of organizational knowledge creation. Different from the case of high complexity of task, the use of both technologies have linear relationships while the complexity of task is relatively lower. So, the decreases of effectiveness by the amount of technology usage do not occur. These results can be the evidence for supporting hypothesis 3-1 and rejecting hypothesis 3-2.

Table 27. Testing result of the hypotheses

Hypothesis 1. The relationship between the use of BDA and the organizational knowledge capability follows an inverted U-shape	
Linear model	$CAP = -2.08 + \mathbf{2.92e^{-01**}Use_{BDA}} \ldots + \mathbf{3.95e^{-01***}X_{ORG\_DIV}}$
	$CAP = -1.47e^{-16} + \mathbf{3.08e^{-01**}Use_{BDA}} + \mathbf{1.21e^{-01*}Use_{OP}} \ldots + \mathbf{4.08e^{-01***}X_{ORG\_DIV}}$
Polynomial model	$CAP = -0.094 + \mathbf{0.327^{**}Use_{BDA}} - \mathbf{0.094^{*}Use^2_{BDA}} + \ldots + \mathbf{0.205^{***}X_{ORG\_DIV}}$
	$CAP = \mathbf{-0.115^{*}} + \mathbf{0.337^{***}Use_{BDA}} - \mathbf{0.084^{*}Use^2_{BDA}} + 0.106Use_{OP} + 0.031Use^2_{OP} + \cdots + \mathbf{0.404^{***}X_{ORG\_DIV}}$
Hypothesis 2. The relationship between the use of online platform and the organizational knowledge capability follows an inverted U-shape.	
Linear model	$CAP = 9.19e^{-17} + 8.44e^{-02}Use_{OP} + \ldots + \mathbf{1.42e^{-01*}X_{ORG_{SIZE}}} + \ldots + \mathbf{5.21e^{-01***}X_{ORG\_DIV}}$

	$CAP = -1.47e^{-16} + \mathbf{3.08}\boldsymbol{e^{-01}}{}^{**}\boldsymbol{Use_{BDA}} + \mathbf{1.21}\boldsymbol{e^{-01}}{}^{*}\boldsymbol{Use_{OP}} \ldots$ $+ \mathbf{4.08}\boldsymbol{e^{-01}}{}^{***}\boldsymbol{X_{ORG\_DIV}}$
Polynomial model	$CAP = -0.057 + 0.075Use_{OP} + 0.058Use_{OP}^{2} + \ldots + \mathbf{0.138}^{*}\boldsymbol{X_{ORG_{SIZE}}} + \ldots +$ $\mathbf{5.20}\boldsymbol{e^{-01}}{}^{***}\boldsymbol{X_{ORG_{DIV}}}$
	$CAP = \mathbf{-0.115}^{*} + 0.337^{***}Use_{BDA} - 0.084^{*}Use_{BDA}^{2} + 0.106Use_{OP}$ $+ 0.031Use_{OP}^{2} + \cdots + \mathbf{0.404}^{***}\boldsymbol{X_{ORG\_DIV}}$

Hypothesis 3-1. The high complexity of task intensifies the effect of the use of *BDA* on the capability of organizational knowledge creation.

Hypothesis 3-2. The high complexity of task intensifies the effect of the use of *online platform* on the capability of organizational knowledge creation.

All	$CAP = -0.115^{*} + \mathbf{0.337}^{***}\boldsymbol{Use_{BDA}} - \mathbf{0.084}^{*}\boldsymbol{Use_{BDA}^{2}} + 0.106Use_{OP}$ $+ 0.031Use_{OP}^{2} + \cdots + \mathbf{0.404}^{***}\boldsymbol{X_{ORG\_DIV}}$
Low complexity	$CAP = -0.175^{*} + \mathbf{0.267}^{**}\boldsymbol{Use_{BDA}} - 0.043Use_{BDA}^{2} + \mathbf{0.182}^{*}\boldsymbol{Use_{OP}}$ $+ 0.073Use_{OP}^{2} + \cdots + \mathbf{0.574}^{***}\boldsymbol{X_{ORG\_DIV}}$
High complexity	$CAP = -0.069 + \mathbf{0.332}^{***}\boldsymbol{Use_{BDA}} - \mathbf{0.140}^{*}\boldsymbol{Use_{BDA}^{2}} + 0.067Use_{OP}$ $- 0.023Use_{OP}^{2} + \cdots + \mathbf{0.205}^{*}\boldsymbol{X_{ORG\_DIV}}$

Table 28. Linear model: The effect of the use of technology

Model	**BDA model**			**Online platform model**			**Unified model**		
Description	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)
	0.4373 (0.4207)	243	<2.2e-16	0.3892 (0.3741)	243	<2.2e-16	0.4439 (0.4278)	242	< 2.2e-16
Items	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)
α	-2.08E-16	4.81E-02	1	9.19E-17	5.00E-02	1	-1.47E-16	4.78E-02	1
Use_{BDA}	2.92E-01	6.29E-02	5.69E-06**	-	-	-	3.08E-01	6.30E-02	1.92E-06**
Use_{OP}	-	-	-	8.44E-02	6.28E-02	0.1805	1.21E-01	6.05E-02	0.0466*
Size	-3.37E-02	6.26E-02	0.590	-1.06E-01	6.69E-02	0.114	-6.78E-02	6.45E-02	0.2938
Org_size	6.14E-02	6.17E-02	0.321	1.42E-01	6.26E-02	0.0238*	7.15E-02	6.16E-02	0.2464
Org_type	3.00E-02	6.35E-02	0.637	1.11E-03	6.71E-02	0.9868	7.76E-03	6.41E-02	0.9038
Ind_cap	-3.39E-02	6.16E-02	0.582	-4.78E-02	6.42E-02	0.4576	-4.22E-02	6.14E-02	0.4922
Org_div	3.95E-01	6.22E-02	1.04E-09***	5.21E-01	6.03E-02	8.01E-16***	4.08E-01	6.21E-02	3.16E-10***

Table 29. Polynomial model: The effect of the use of technology

Model	BDA model			Online platform model			Unified model		
Description	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)
	0.4505 (0.4346)	242	<2.2e-16	0.3892 (0.3741)	243	<2.2e-16	0.4592 (0.4393)	240	< 2.2e-16
Item	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)
α	-0.09374	0.05935	0.11556	-0.0579	0.06605	0.3816	-0.11509	0.06815	0.0926*
Use_{BDA}	0.32777	0.06363	5.37E-07**	-	-	-	0.33729	0.0639	2.92E-07***
${Use_{BDA}}^2$	-0.09412	0.03566	0.00884**	-	-	-	-0.08379	0.03652	0.0226*
Use_{OP}	-	-	-	0.075	0.06311	0.2358	0.10698	0.06035	0.0775
${Use_{OP}}^2$	-	-	-	0.05813	0.04339	0.1816	0.03176	0.04223	0.4528
Size	-0.03049	0.06181	0.62229	-0.1153	0.06716	0.0873	-0.06758	0.06427	0.2941
Org_size	0.06186	0.06098	0.31139	0.13872	0.06252	0.0274*	0.06945	0.06097	0.2558
Org_type	0.03166	0.06277	0.61445	0.01234	0.06746	0.855	0.01695	0.06397	0.7913
Ind_cap	-0.04527	0.06102	0.45891	-0.04444	0.06413	0.489	-0.04992	0.06098	0.4139
Gen_ratio	0.39136	0.06144	9.48E-10***	0.52061	0.06023	7.55E-16***	0.40412	0.06154	3.16E-10***

Table 30. Mediating effect of task complexity

Task complexity	High Complexity			Low Complexity			Unified model		
Description	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)	R-squared (Adj)	df	P-value (F-stat)
	0.3364 (0.2845)	115	<2.026e-07	0.3892 (0.3741)	116	<2.2e-16	0.4592 (0.4393)	116	< 2.2e-16
Item	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)	Coeff.	Std. err	Pr(>|t|)
α	-0.0695	0.09953	0.48642	-0.17501	0.090175	0.05471*	-0.11509	0.06815	0.0926*
Use_{BDA}	0.33204	0.10043	0.00126**	0.267819	0.082749	0.00158**	0.33729	0.0639	2.92E-07***
${Use_{BDA}}^2$	-0.14019	0.07018	0.04812*	-0.043028	0.042335	0.31156	-0.08379	0.03652	0.0226*
Use_{OP}	0.06701	0.09014	0.45873	0.182298	0.082481	0.02906*	0.10698	0.06035	0.0775
${Use_{OP}}^2$	-0.02371	0.06365	0.71019	0.073549	0.059406	0.21819	0.03176	0.04223	0.4528
Size	-0.13214	0.0986	0.18283	-0.02004	0.082233	0.80788	-0.06758	0.06427	0.2941
Org_size	0.11955	0.09342	0.20325	0.056162	0.07866	0.47667	0.06945	0.06097	0.2558
Org_type	-0.06428	0.09842	0.51499	0.000919	0.084387	0.99133	0.01695	0.06397	0.7913
Ind_cap	-0.02069	0.09409	0.82635	-0.04052	0.079453	0.61099	-0.04992	0.06098	0.4139
Gen_ratio	0.20546	0.1009	0.04401*	0.574513	0.079561	5.81E-11***	0.40412	0.06154	3.16E-10***

5.4 Discussion

This study carried out two analyses to determine the impact of the use of technology on the behavior of knowledge generation in the organization. The first analysis carried out statistical estimates through linear and polynomial regression models to capture the impact of BDA and online platform usage on the organization's knowledge creation capability. The first analysis provided empirical evidence of support for hypothesis 1 and the rejection of hypothesis 2. In other words, the use of the BDA was found to have an inverse u-shaped relationship with the ability of the organization to generate knowledge, while it was concluded that the online platform did not have a significant impact.

In general, the use of BDA technology has been known to enhance the organization's analytical capabilities and play an important role in discovering the information or knowledge (Agarwal, Gao, DesRoches, & Jha, 2010; Goh, Gao, & Agarwal, 2011; Ker, Wang, Hajli, Song, & Ker, 2014), which is hard to retrieve, through various data that humans cannot handle (Brynjolfsson & McAfee, 2011; Gillon, Aral, Ching-Yung, Mithas, & Zozulia, 2014). However, the results of this study suggest that degree of use is also important in the use of emerging technologies (Devaraj & Kohli, 2003). Proper use of technologies can help organizations create valuable knowledge for acquiring the competitive advantage (Dewan, 1997; Diewert & Smith., 1994; Hitt, L., 1995; M. Kelley, 1994; Siegel & Griliches., 1992). This is because the technological factors can handle tasks more efficiently. However, excessive use of technology can have a negative impact (Baily, 1986; Barua, Kriebel, & Mukhopadhyay., 1995; Roach, 1987; Strassman, 1990). First of all, excessive use of technology results in organizational dependence on technology and sometimes, this dependency can serve as a huge obstacle (Will, 1991)endence. When faced with similar problems, organizations should make decisions based on a variety of factors, including contextual conditions, environments, and goals at the time. However, intensified dependence on technology can make humans overlook the consideration of various external and subjective factors that can be perceived by humans. In this case, organization is likely to stay in local optimums that are far from ideal solutions. To sum up, the use of technology should involve a certain level of human intervention.

Another side effect of excessive use of technology is the attenuation of organization survivability. Dependence on BDA technology can significantly reduce the frequency of important organizatinal behaviros in the process of organizational knowledge creation, such as discussions, exploration and consensus among members (Woodman et al., 1993). Although the performance of the BDA in the short term seems to be more efficient and better than the organizational behavioural methods, it can be negative from a mid- to long-term perspective. First, the environment surrounding the organization changes fast and dramatically. Environmental changes, especially in modern society, are unprecedentedly fast and broad. So, adaptation to these changes requires the production of new knowledge, paradigms, perspectives, and so on, which organizations are forced to be highly flexible to survive. The most effective way to ensure organizational flexibility lies in the accumulation of creative and diverse knowledge resulting from interactions among members, rather than using techniques such as BDA. Securing organizational diversity, in particular, prevents organization from becoming entrenched in the impasse that is called 'genetic equilibrium' in the evolutionary process (Holland, 1992). That is, the diversity of people and the occurrence of new mutations may ensure the minimum organizational diversity to respond to environmental changes.

On the other hand, the use of online platforms did not have a significant relationship with the ability to create organizational knowledge. There can be three main reasons for this.

The first is that the use of online platforms is no longer new. Online platforms are effective channels for sharing knowledge and information without time and spacial constraints. Therefore, the use of online platforms has become one of the natural skills of organizational members in modern organizations, and as a result, the use of online platforms has become one of routines. This phenomenon means that organization members no longer use online platforms as a strategic method.

The second reason is that the use of online platforms includes substantial non-task aspects. The purpose of using an online platform is in enhancing the productivity, such as acquiring information, sharing knowledge, and so on, but at the same time, it is often used for personal enjoyment and satisfaction. For example, having access to new news on an online platform has the effect of acquiring information, but at the same time there is also the satisfaction of having access to various comments or related information on the news. In other words, since the use of online platform is a mixture of personal satisfaction and enjoyment, it can be impractical to fully use online platform for achieving organizational goals.

The last reason lies in the inherent limitations of online platforms: reliability and verification. Reiliability and justification of information are important issue for avoid a false dependence on technology (R. J. Aldag & Power, 1986). The online platform contains a vast amount of knowledge and information, but in practice, accurate evaluation and filtering of them should be followed directly by those who is going to adopt it. That is why people may feel that already assessed and widely used knowledge is more useful than an online platform involving uncertainties and distrust coming from the lack of evaluation. Thus, even if new information or knowledge can be obtained from the online platform, it is necessary to be verified and reviewed by BDA technology or organizational interaction.

The second analysis aims to identify the mediating effects of task complexity. To achieve this objective, this study conducted an analysis by dividing the sample into two groups based on the average task complexity score. The findings of the second analysis conflict to the field study result in McHugh et al. (2016) that the high task complexity reduce the importance of collective intelligence. In other words, the properties of technology and the tasks should be fitted by apprioate method and qulified people (Goodhue & Yompson, 1995). However, if the task is not complex (e.g., low interdependencies, the result of this study support the simulation result of McHugh et al. (2016). The importantce of discussion or interaction are decreased but the effectiveness of formalized processes is increased such as BDA and online platform (Malone & Bernstein, 2015; Argote, 1982).

The findings of this study can contribute to establishing strategies for the use of technology in knowledge management perspective. The role of the system in knowledge management is very important. In practice, however, how organizations use the system can be completed through accumulated experience and know-how through trial and error. This study can reduce these risks from trials and errors in organizations and give meaningful messages in developing strategies for using BDA and online platform technologies more efficiently. Further, the study could provide a empirical basis for bringing high success rates and productivity in designing organizations in terms of socio-technical design, through providing links between technology and human behavior.

Chapter 6. Conclusion and implications

6.1 Conclusions

6.1.1 Overall summary

This study was aimed at exploring the creation of knowledge within an organization around the concepts of groupthink and collective intelligence, and to present strategies that could improve the creation of organizational knowledge from the perspective of self-organization. In order to reach these goals, we focused on the mechanism of the emergence of groupthink, the interconversion between groupthink and collective intelligence, and the exploration of strategies for improving organizational knowledge creation.

(1) Chapter 3: Is groupthink really inevitable?: based on self-organization aspect

Chapter 3's study titled "Is groupthink really inevitable?: based on self-organization aspect" identified criticism of existing groupthink models and suggested alternative model in terms of self-organization. The findings in this chapter give meaningful implications. Janis' model of groupthink can explain the occurrence of groupthink, but does not explain how groupthink exacerbate the outcomes of an organization. In other words, the Janis model did not show that groupthink reduces the quality of organizational output. However, the findings in the alternative model of this study presented a different perspective. First of all, groupthink is not caused by a combination of the antecedents, but rather by the interaction of members within the organization. In this process, the antecedents of Janis model showed a different effect from the original argument. It has been shown that group cohesiveness, the key factor in Janis model (Miranda & Saunders, 1995; Tetlock, 1979), does not significantly affect the occurrence of groupthink. These results were consistent with existing findings of the previous studies (e.g., Callaway & Esser, 1984; Courtright, 1978; Flowers, 1977; McCauley, 1998; Turner & Pratkanis, 1998c), but this study found additional characteristics of group cohesiveness. The ABM simulation results reported that group cohesiveness does not aggravate organizational performance in static environments, but in the dynamic and fluctuant environment, it can weaken the organization's resilience, resulting in a rapid decline in organizational performance. Previous groupthink studies explained this loss of resilience as a concept of a temporary organization. Bourgeon (2007) presented that groupthink can be emerged by the initial setting casuing the group cohesivenes. Therefore, increasing the adaptibility toward unexpected events through heterogeneity and creativity of temporary organizations can be an effective solution for groupthink phenomenon (Hällgren, 2010; Lindkvis, 2005). Based on this idea, they argued that temporary or autonomous organization can reduce the groupthink. However, previous could not capture why the organizational adaptibility can enhcance because the studies just based on selected cases which are so specific. At this point, this study provides a novel idea that group resilience may depend on group cohesiveness. Also, structural faults of Janis' model have been shown to significantly weaken organizational performance (McCauley, 1989). n terms of the organizational resilience toward the environment, structural faults can overwhelm the positive effect of the temporary organization involving heterogeneity, creativity, and bring the negative consequences of groupthink phenomenon (Ekstedt, Lundin, So¨derholm, & Wirdenius, 1999; I. L. Janis, 1982; Lundin & Söderholm, 1995; PMI, 2004). The result of this study showed that structural fault almost eliminates the resilience of an organization and leads them to the low-performance situation.

In sum, the cause of groupthink lies in intra-organizational interaction, and groupthink is not the dominant factor of the organization's performance. However, structural faults can significantly worsen the organizational performance. Also, group cohesiveness can lead to temporary deterioration of organizational performance due to a decrease in the organization's environmental adaptability when environmental changes are rapid.

(2) Chapter 4: The optimal knowledge creation strategy of organizations in groupthink situations

The second study, "The optimal knowledge creation strategy of organizations in groupthink situations" is in chapter 4. This study explored ‘switching factor’ transforming groupthink into collective intelligence, and proposed the efficient strategies for organizational knowledge creation. This study carried out two main analyses through an ABM simulation and meta-frontier analysis: examining the effect of switching factor and comparison of the strategic efficiency. The switching factors, a key concept of this study, was derived from the intersections of relevant previous literature. The solutions of groupthink and the conditions for collective intelligence were aggregated and overlapping or similar concepts were paired into three types. The switching factors consist of knowledge conflict, reconsideration of alternatives, and organizational memory, and each factor is shared between the solutions of groupthink and the determinants of collective intelligence.

Three independent analyses were performed through ABM simulations to capture the effect of switching factors on organizations mired in the groupthink situation. Knowledge conflicts resulted in a high level of improvement in organizational performance based on a reference model without switching factors but resulted in a rapid loss of diversity. This result implies the reason that knowledge conflict is not enough to achieve organizational improvement (Ames & Murray, 1982; Piaget, 1977) despite it is a good method for finding the optimal knowledge(Schoonhoven, Eisenhardt, & Lyman, 1990) . When knowledge conflict exists without any other interventions, organizations try to resolve conflict because of the cost of conflict, and groupthink appears during this point (Ames & Murray, 1982; Golkar, 2013; Hällgren, 2010; Karen A Jehn, 1995). That is why knowledge conflict dramatically increases the knowledge bias, which is the organizational diversity of knowledge. Turner & Pratkanis (1998a) suggested that one more factor has to be required for constructive knowledge conflict, which is 'reflection of opposite ideas'.

The reconsideration of alternatives model supports to the idea of Turner et al. (1998a). Reconsideration of alternatives resulted in preserving diversity of an organization, while only a slight improvement in organizational performance. In terms of collective intelligence, reconsideration of alternative is matched the evaluation process of individual knowledge because reconsideration is one of the factors to distinguish wisdom of crowd from collective intelligence (Choi, 2009). In addition, on groupthink perspective, reconsideration of alternatives the illusion of blind conformity to organizational opinions (Flippen, 1999) based on the diversity of organizational knowledge (Robbins & Judge, 2013).

To maintain the diversity of organizational knowledge, the reconsideration of alternatives is not enough because it can only target the existing knowledge or ideas in the organization. So, an organization requires a method to keep the passed or ignored knowledge regardless of time or turnovers (Ackerman & Halverson, 1999; Spender, 1996). Organizational memory is an effective way for that (Kruse, 2003). According to the reults of this study, organizational memory played a role in significantly improving the performance of an organization before a certain period, but over time showed a lower level of organizational knowledge than the reference model. However, the reulst of this study seems to be contradictory to the existing studies. In other words, the early stage result of this model supports a viewpoint that organizational memory is a necessary procedure organizational performance (e.g., K. Lee, Kim, & Joshi, 2017), but later stage's result emphasizes the negative influence of organizational memory (e.g., Starbuck & Hedberg, 1977). This study suggests a plausible idea to compromise these conflict perspectives.

What is unique point of organizational memory model did not preserve the diversity of individual knowledge, but formed an island-like independent knowledge domain. At the early stage of organizational knowledge creation process, acquisition and maintenance of knowledge through organizational memory are curicial for successful deployment of organizational knowledge creation (Abecker & Decker, 1999). Over time, however, the amount of knowledge accumulated in organizational memory gradually increases and finally the amout of organizational memory will exceed the capability of retireving required knowledge. As a result, organizations can not explore stored knowledge effectively, organizational memory can cause deterioration of organizational performance by making the organization lose the correct direction. To sum up, organizational memory can have a positive effect on organizational knowledge creation only when an organization's retreiving capability exceeds the amount of stored knowledge.

The results of this study also indirectly suggest organizational differentiation. According to the analysis results, organizational memory currently separates the knowledge of the organization into two domains. That is to differentiate knowledge within an organization into two disparate groups. Final organizational decisions converge into knowledge domains supported by more members, and this biased process may decerease the quality of organizational knwoledge. Different to the previoust studies on the organizational polarization emphasizing the attitude and behavior (Brauer, Judd, & Gliner, 2006; Myers & Lamm, 1976), social identity (Mackie, 1986; Hogg & Turner, 2010), fear and loathing (Iyengar & Westwood, 2015) and etc., this study finds out a plausible reason of polarization from the organizational memory.

Previous studies on both groupthink (e.g., Lee et al., 2016; Rajakumar, 2019) and collective intelligence (e.g., Bates & Gupta, 2017a; Massari et al., 2019; A. W. Woolley et al., 2010; Anita Williams Woolley et al., 2015) have focused on the effect of single factor than the combination of multiple factors. The study of groupthink put much effort into multidimensional measurement of factors (e.g., Riccobono et al., 2016; Casey-Campbell & Martens, 2009; Chapman, 2006; Erdem, 2003; Turner & Pratkanis, 1998a), but did not identify the change in the occurrence of groupthink due to the combination of various factors. Also, collective intelligence researches have more emphasized 'which system is more effective for collective intelligence'(e.g., De Vincenzo et al., 2018; Reia et al., 2019; Tao, 2018) rather than fundamental issues such as 'what is the source of collective intelligence?'. The result of second study in chapter 4 presents the missing block between two perspectives.

The second analysis compared the efficiency of the strategies involving the combination of switching factors by meta-frontier analysis. This analysis showed that the strategy combining knowledge conflict and alternative reconsideration represented the highest efficiency, whereas the strategy involving only the reconsideration of alternatives showed the lowest efficiency. Although all strategies showed higher efficiency than the reference model without any strategy, relative differences clearly existed. What does this result mean? As metioned before, each switching factor has its speicial role in the organizational knowledge creation.

Knowledge conflicts have been effective in the efficient convergence of organizational knowledge and in exploring optimal solutions (Ames & Murray, 1982; Piaget, 1977), and explore various pools of knowledge held by members who are trying to reconsider alternatives to increase the accuracy of the organizational exploitation (Turner & Pratkanis, 1998a). Finally, organizational memory serves to expand the scope of the exploration for successful organizational knowledge creation by accumulating knowledge generated by individual members (Abecker & Decker, 1999). From this point of view, the results of the Meta-frontier analysis of Chapter 4 can be explained in three aspects for the creation of knowledge: effectiveness, accuracy and diversity. In this study, the combination of effectiveness (knowledge conflict) and accuracy (reconsideration) was found to be the most efficient knowledge generation strategy. Through knowledge conflict, the knowledge that is likely to be answered is screened, and this process is repeated several times until more accurate organizational knowledge are obtained. Indeed, the combination of these two aspects is one of the main strategies for promoting collective intelligence (e.g., Ahn and Lee 2009; Denning et al. 2005; Levy 1994). Therefore, the results of this study may be evidence supporting the existing frameworks for generating collective intelligence. Another point to note is that this strategy has higher efficiency than a strategy that includes all three factors. In this study, we guessed that the organization's ability to retrieve knowledge was a matter. In other words, if an organization has a higher capability of retrieving knowledge than the amount of it, strategy utilizing all three factors can have a greater efficiency. However, since the ABM in this study set up the behavior of retrieving knowledge by random, that case cannot be excluded.

The findings of Chapter 4 suggest two implications. First, the reconsideration of alternatives may be the most important factor in designing an organizational knowledge creation strategy. Although the reconsideration of alternative referred to the lowest level of efficiency when used alone, it has always shown highe efficiency when used in combination with other switching factors. In other words, the positive effects of reconsideration are amplified through interaction with other factor. However, if an organization is considering a strategy with a single switching factor, knowledge conflict or organizational memory can be a more effective strategy.

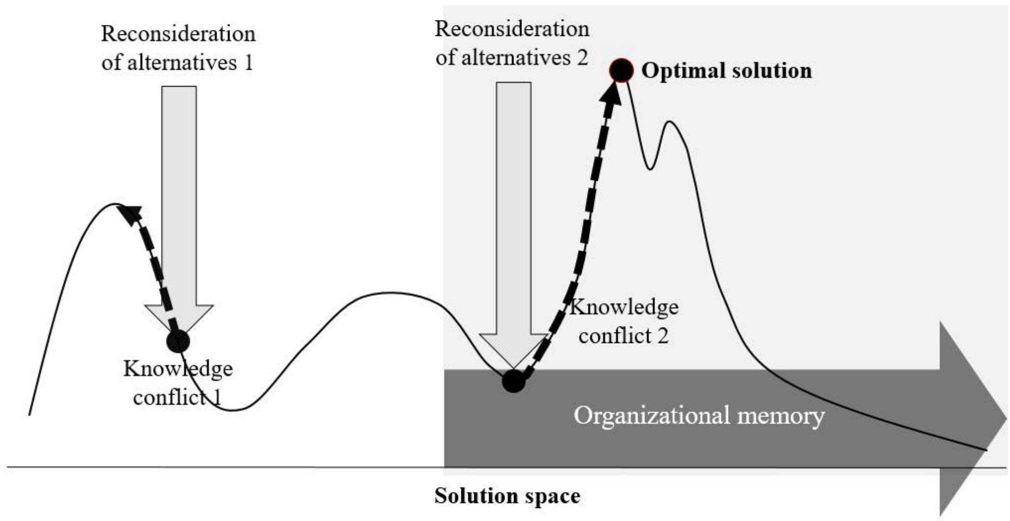


Figure 31. The role of each switching factor in the organizational knowledge creation process

(3) Chapter 5: Effect of emerging technologies on the organizational knowledge creation: the use of big data analytics and online platforms

The last study, "Effect of emerging technologies on the organizational knowledge creation: the use of big data analytics and online platforms," is a socio-technological approach to an organization's ability to create knowledge. The goal of this study is to identify the relationship between the two main technologies and organization's capability to create knowledge. In addition, by identifying the mediating effect of task complexity in these relationships, changes in the influences of the uses of technologies were examined through the task complexity.

This analysis captured the effects of the use of both technologies on organizational knowledge creation capabilities through simple linear regression models and polynomial regression models. Although the use of technology can help improve the performance and efficiency of an organization in general situations (Alavi & Leidner, 2001; Faraj et al., 2011; Täuscher, 2017), but it is likely to have opposite effects if they are used excessively or incorrectly (Kamel & Quintana, 2013; Von Krogh, Ichijo, & Nonaka, 2000). Therefore, in this study, it was assumed that the use of technology and the creation of organizational knowledge would have an inverted U-shaped relationship, and that high task complexity can further strengthen this relationship (Chiocchio, 2007; Langfred & Shanley, 1997; McHugh et al., 2016). The results of analyses showed that the use of BDA and the creation of organizational knowledge satisfied the inverted U-shaped relationship, but the use of online platforms did not have a significant relationship with organizational knowledge creation capability. Obviously, BDA technology is an effective way to support human decision makings and knowledge creation (Malone & Bernstein, 2015), thus this result is natural. However, online platform does not impact of the capability of organizational knowledge creation contrary to the result of previous studies supporting the positive effect of the use of online platforms on the organizational performance (Ma, M., & Agarwal, 2007; Ikujiro Nonaka et al., 2006b; O'mahony & Ferraro, 2007; Tapscott & Williams, 2006). This study proposes two possible explanation for that. First, the knowledge coming from the online platform is not reliable enough to use. The relaiability of information in the online space has been considered as an importanat issue. According to the previous studies, information or knowledge from the online platform fundamentally have limitations in their reliability because of two reason. The first reason refers to the anonymity of online space. Since organiations are likely to trust knowledge generated internally (Flippen, 1999), they request reliable evaluation toward the external knowledge. Malone & Bernstein (2015) suggested that the reliability of knowledge from online platform is depend on the reliability of source of knowledge and knowledge itself. However, most of online platform do not have both type of reliability because of their costs. In order to obtain these reliability, each online platfrom has to secure a certain level of transparency (Prahalad & Ramaswamy, 2004) and peer evaluations (Flanagin & Metzger, 2000; Flanagin & Metzger., 2008). However, anonimity of online platform seriously inhibit these actions because it attenates individual responsibitilty toward the accuracy of information or knowledge (Faraj et al., 2011; Rains, 2007). That is one reason that online platforms do not affect to the organizational knoweldge creation capability.

The second reason lies in the excessive amount of knowledge and information in the online platforms. Bounded rationality of people narrowed the scope of exploration. So the group people actually communicating is much smaller than the whole size of network (Koohborfardhaghighi et al., 2017). Consequently, organization depend on the decision of individuals that looks like a random sampling, when the volume of knowledge exceed the capability of organization, thus it is difficult for organizations to utilize online platforms as a source of knowledge (Lane, Koka, & Pathak, 2006). Although organizations can acquire this ability through the accumulation of prior knowledge (Lichtenthaler & Lichtenthaler, 2009), this ability request considerable costs such as time and money (Gebregiorgis & Altmann, 2015; Haile & Altmann, 2016).

However, if the task complexity is relatively low, both the use of the BDA and online platform monotonously impacted on the capability of organizational knowledge creation. In other words, the more technology is used in low-complexity situations, the better the knowledge creation capability regardless of the intensity of use. This can be explained in terms of socio-technological view. A complex task requires high level of interaction between technololgy and humans (Pidgeon & O'Leary, 2000; Turner, B.A., Pidgeon, 1997). Previous studies pointed out two aspect inducing the inefficiency of the use of BDA in high complexity tasks. First aspect is related to the prior-decision making of organization. When the task is highly complex, the uncertainty of solution is increased (McCauley, 1998), so some specific domain that we should focused is decied by human decision making process (Longley, J., & Pruitt, 1980). In other words, if the complexity of the task increases, the amount of essential decisions that people have to conduct. Another reason is that high task compelx requires high collective intelligence involving interactions among people. Despite the analysis itself is conducted by computers or machines, details such as what should be input, which algorithm should be used, or how to interpret the results belong to the human's role. Previous literature emaphsize that knowledge collaborations using various knowledge background are required to complete very complex tasks (e.g., Chiocchio, 2007; Hansen & Vaagen, 2016; Surowiecki, 2004). Conversly, if the complexity of task is decreased, the importance of the role of humas is also diminshed. That is why the use of tehcnology monotonously increase the capability of organizational knwoedge creation under the low-complexity task situations.

These findings brought some implications for the use of BDA and online platform technologies. Although the BDA should maintain an appropriate level of use in general situations, it may be good to fully use it for low-complexity tasks. However, while the use of online platforms is difficult to consider as a strategic way to solve the problem of high business complexity, increasing usage with the BDA may contribute to improving organizational knowledge creation capabilities.

6.1.2 Main findings

This dissertation discovered the four major findings described as below.

i. Groupthink is a result of organizational interactions, and a natural step for creating a new knowledge or decision making.
ii. Thus, groupthink can be transformed into a more productive form such as collective intelligence, and vice versa.
iii. Reconsideration of alternatives is an essential component for efficient strategies to enhance organizational knowledge creation
iv. The use of BDA is beneficial for organizational knowledge creation capability but excessive use of BDA should be avoided.

6.2 Implications

The results of this dissertation can be aggregated to present a step-by-step strategy for the organizational knowledge creation process. The process of creating knowledge can be divided into 'Step 1: Individual Knowledge Interaction', 'Step 2: Integration of Knowledge' and 'Step 3: Decision'. Each step is divided by the form of knowledge it interacts with and how it interacts.

i. **Step 1:** In individual knowledge interactions, knowledge is regarded as a unique resource held by an individual. Knowledge at this time exists regardless of the role of the individual or the goals of the organization as the raw knowledge possessed by the individual through private channels. This knowledge is called initial knowledge here. This initial knowledge is shared and transformed within the organization through the social interaction between individuals. Step 1 is this process, where free interaction occurs because there are no specific organizational goals or personal uses associated with initial knowledge.

ii. **Step 2:** In the integration phase of knowledge, the goal of the organization becomes clear, and individual utility also arises accordingly. From this stage, the members of the organization evaluate their individual knowledge and perform strategic interactions on their unique criterion. In other words, people share and combine knowledge in a way that increases their utility or the other objective functions. Thus, selective interaction occurs at this stage, and the form of knowledge converges around the local optimum.

iii. **Step 3:** The decision-making stage is centered on organizational evaluation and decision rather than interaction between individuals. Thus, the quality of integrated knowledge becomes more important than the quality of individual knowledge at this stage.

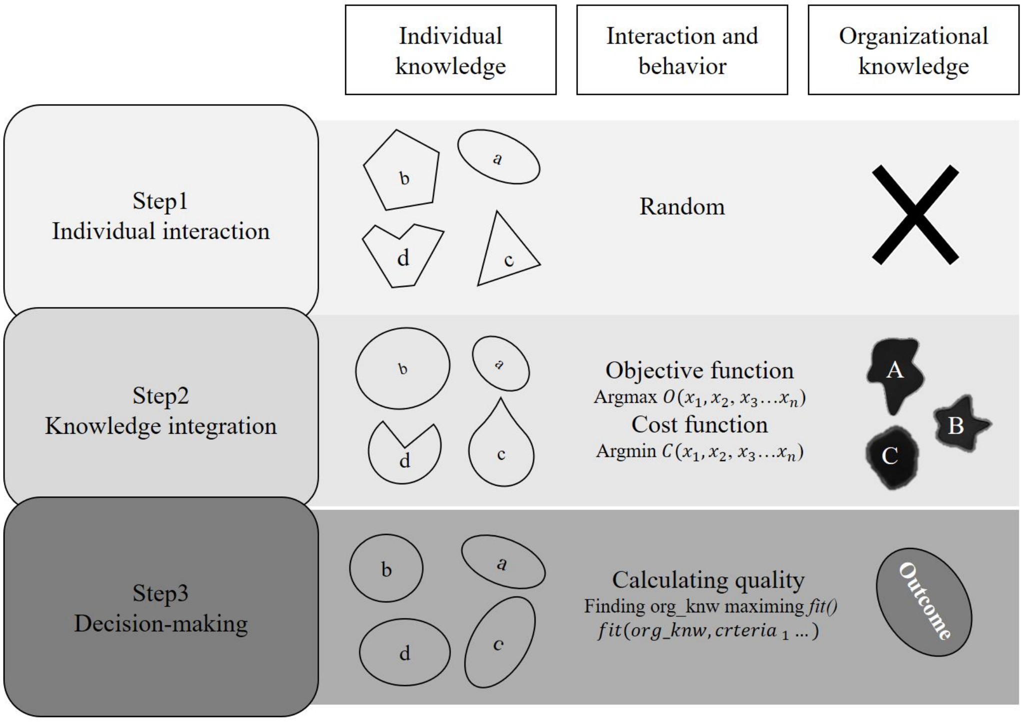


Figure 32. Organizational knowledge creation process

Since all the bases of knowledge used from the second stage are formed at this stage, the creation and accumulation of large amounts of knowledge at this stage can be directly linked to the organizational performance. For example, if an organization developing a new smartphone does not have the sharing and accumulation of knowledge related to the smartphone, no amount of discussion and evaluation can have much effect. As mentioned earlier, organization does not intervene to the acquisition of initial knowledge held by each member. As a result, the part where an organization's capabilities can actually be requested is the interaction of initial knowledge. Because no objective function exists at this stage, each person chooses their interaction partner and content based on their social and personal preferences. So, organizations should provide physical places, systems, etc. where these actions can occur actually. It is required to provide physical support such as a lounge for various members to converse and share information in the building, supports for social club activities unrelated to work, and online messengers and bulletin boards for anonymous communication within the organization. These organizational activities can lead to high knowledge diversity ahead of the genuine organizational knowledge creation process. Also, these can create clusters among organizational members to increase solution exploration efficiency of each member.

When an organization's goals are set according to the demand of the environment or the vision of the organization, various detailed objectives are also esatblished. Each organization should stack and integrate knowledge dispersed across the organization to fulfill their given goals. During this process, the integrated knowledge is not formed as an independent knowledge, but is represented as the interaction and combination of diverse knowledge. Although there are many strategic organizational actions required in this stage, this disseratation focused on switching factors. The process of integrating knowledge naturally leads to organizational bias. This bias is neutral, and the quality of this biased knowledge becomes clear after the decision making is completed in the next step. However, the results of my thesis suggested that switching factors improve the creation of organizational knowledge. The role of the switching factor in Phase 2 is to increase the likelihood that biased knowledge can be formed close to the achievement of the best solution, that is, the goal of the organization. According to the results of Chapter 4, this includes knowledge conflict, reconsideration of alternatives, and organizational memory. Among them, the combination of alternative reconsideration and other factors could be the most efficient strategy.

In the final stage, called decision-making phase, the criteria for knowledge evaluation become very important. Even if the organization sets a very clear and objective goal, it is impossible to define the best knowledge to achieve this goal. Because, despite an organization knows its own objective function, but does not know in advance the ideal solution for maximizing it. This step requires the organization to determine what knowledge can be achieved the goal among the groups of potential optimums with the highest probability. If the tasks that organizations must deal with are simple, the identification of optimal knowledge becomes very easy. For example, knowledge of an firm's financial status, market share, and consumer responses is easy to collect and distinguish. It is also easy to determine by various criteria whether the organizational solution matches the ideal one. However, it is hard to derive optimal knowledge if the tasks are abstract and complex, such as designing new business model, developing new technologies/new products, and marketing strategies. In order to achieve this goal, it is best strategy for organizations to choose the solution that is most likely to succeed. From now, how to make a good criteria becomes matter. This dissertation pointed out the role of technology in this process. In particular, BDA technology can provide effective evaluation criterion through its advantageous characteristics. The use of BDA has advantates in discovering hidden patterns and phenomena that humans cannot recognize in massive repositories of information and knowledge. Although the results of utilizing BDA do not reflect social factors such as the vision, context, and culture of the organization, they are worth as the criteria for assessing the performance of the integrated knowledge. Thus, at this stage, the organization is requested to acquire enough knowledge or information that can serve as the basis for decision-making considering social aspects like the psychological, subjective, and cultural contexts that are technically difficult to determine.

6.3 Utilization

Collective intelligence is required in organizations at various levels. Promoting collective intelligence becomes difficult as the group grows in size, as uncertainty and complexity increases. Thus, applying the same strategy to organizations of all sizes can sometimes be wasteful, and there is the possibility of unnecessary processes being counterproductive to the organization. Nevertheless, guidelines for collective intelligence can play an important role in creating and innovating organizational knowledge.

6.3.1 Firm

A company is an organization with a special purpose of seeking profit. Maximizing corporate profits is directly related to increasing the utility of its members, which drives the survival, growth and innovation of firms in terms of mid- to long-term. Modern companies have been focused on the creation of knowledge to achieve these goals. This is because knowledge is the most powerful way to gain competitive advantage over other companies. The theoretical basis for the creation and management of knowledge of firms varies widely. However, this study could present a practical strategy from a slightly different point of view. First of all, the importance of actual use of intra-organization failures is critical. The results of this paper is that a key strategy is to revisit and utilize failed experiences, excluded knowledge and information. Therefore, it is necessary to set up a specialized department to explore solutions only based on the company's failed data, or to set up a procedure to reconsider the excluded knowledge on the existing task process. Another effective method is to prepare guidelines for the use of decision-support technology according to the type of work. If no guidelines exist for the use of technology, members may be confused about how far to deal with a person's domain when working in detail. In other words, deciding which issue to decide on is to be discussed or dealt with the help of other technologies is a part that must be decided in advance. Therefore, designing proactive guidelines by separating the human domain from the technological domain according to the type and complexity of the task can improve the organization's ability to create knowledge.

However, behind the creation of organizational knowledge and the development of collective intelligence, the side effects of groupthink are likely to coexist. This problem can bring failure to the firm, and the cumulative failure will make it difficult to ensure the survival of the organization. Because of the risk of such groupthink, the corporate has made a great deal of effort to eliminate groupthink from within the entity. Actually, however, it is impossible to block all the cause of groupthink, and the findings provide the opinion that it may not be such an effective method. This means that when a firm designs a solution to groupthink phenomenon, it may not be appropriate to place that objective on the complete elimination of groupthink. Rather than eliminating the phenomenon of groupthink, it is more effective to prevent factors that lead to organizational failure. To this end, the firm should focus on prevent is structural faults. If structural faults are eliminated, groupthink is unlikely to pose a major threat to the success of the enterprise, furthermore a necessary process for the emergence of collective intelligence.

6.3.2 Policy

Organizations that establish policies differ in nature from organizations such as companies and laboratories. It is very difficult to control a single decision completely because different organizations and agencies are linked. Thus, preventing structural defects or presenting technical use guidelines through a package of guidelines, such as an enterprise, can be a costly or difficult goal in reality. Therefore, a slightly different approach is needed.

Various interests must be addressed in order to establish policies. These interests are larger and more complex than those of the firms. Therefore, many policies fail to coordinate them, often resulting in the loss of their original objectives. As a way to prevent these problems, this study suggests the occurrence of intentional groupthink. In the view of previous groupthink theories, it was considered an act that worsened the performance of the organization. However, this study found that there is a large role of structural faults between groupthink and organizational failure. And furthermore, it has been shown that groupthink organizations can secure collective intelligence through appropriate strategies involving switching factors. Therefore, we can minimize interest conflict and increase efficiency by intentionally generating groupthink in the policy-making stage where opposite interests strongly conflict. For example, it is the inducement of groupthink through group cohesiveness, structural defects and provocative contexts between those who oppose and those who support a certain policy. And after consensus has been reached through groupthink, the process of designing the content of detailed policies should ensure that factors (structural flaws, provocative contexts) that have a negative effect on organizational performance are quickly eliminated so as not to fall into the trap of groupthink. Finally, by maximizing collective intelligence through strategies using switching factors, organizational capabilities are fully used to enhance the quality of policies rather than to tune up the conflict interests.

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Appendix

Appendix 1: Questionnaire of chapter 3

PART1: Demographic information

P1. What is the age of the respondent?

____

P2. What is the gender of the respondent?

1	2
Male	Female

P3. What is the final education of the respondent?

1	2	3	4
High school	University	Master	Ph.D

P4. What kind of organization are you belonged to?

1	2	3
Firm	Public organization	R&D Institute

P5. What kind of task are you doing?

1	2	3	4	5
Administration	R&D	Marketing	Distribution	Etc

P6. What is the position of the respondent?

1	2	3	4	5
Part time	Employee	Manager	Board	Etc

P7. What is the size of your organization?

1	2	3	4	5
Under 10	10~50	50~150	Over 150	I don't know

P8. What is the size of your organization?

____

P9. How long did you work in this organization?

____

P10. What is your average monthly income? (Unit: Won)

____

PART2: Antecedents of groupthink

(1) Group cohesiveness

GC_01. There is a high degree of intimacy between the members of my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GC_02. I feel a high sense of belonging to my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GC_03. I want to remain a member of the organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(2) Structural faults

SF_01. There is no leadership in the organization that I belong to.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SF_02. My organization is disconnected from outside information or evaluation.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SF_03. There is no systematic evaluation process in my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SF_04. Members of my organization have a similar background.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(3) Provocative context

PC_01. My organization is under pressure from outside competitors.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SF_02. Members of my organization have low self-esteem due to frequent failures, poor performance.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SF_03. There is a moral dilemma in my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART3: Symptoms of groupthink

(1) Overestimation

OE_01. Risk in successful organizational cases is not considered important.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OE_02. My organization think risk is not matter because the organization capability is competent.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(2) Closed-mindedness

CM_01. I think the decision made by my organization is reasonable.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

CM_02. Our organization is far superior than other competing organizations think.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(3) Uniformity pressure

UP_01. The ideas different to organizational opinions are filtered by the members themselves.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

UP_02. My organization seeks systematic unanimity in most of case.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

UP_03. My organization puts pressure on dissenters.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART4: Symptoms of defective decision makings

SD_01. There is insufficient consideration for the alternative.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_02. No precise search is made for the goal.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_03. Risk of preferred alternatives within the organization is not recognized in advance.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_04. Not enough information is collected for decision making.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_05. Consideration is not given to the Contingency Plan.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_06. External evaluations are not accepted for organizational decision makings

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

SD_07. Alternatives once excluded are not reconsidered.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART5: Quality of decision

QD_01. Organizational members are satisfied with the organization's decision-making.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

QD_02. Our organization's decision-making brings economic benefits.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

QD_03. The decisions our organization has made are very reasonable.

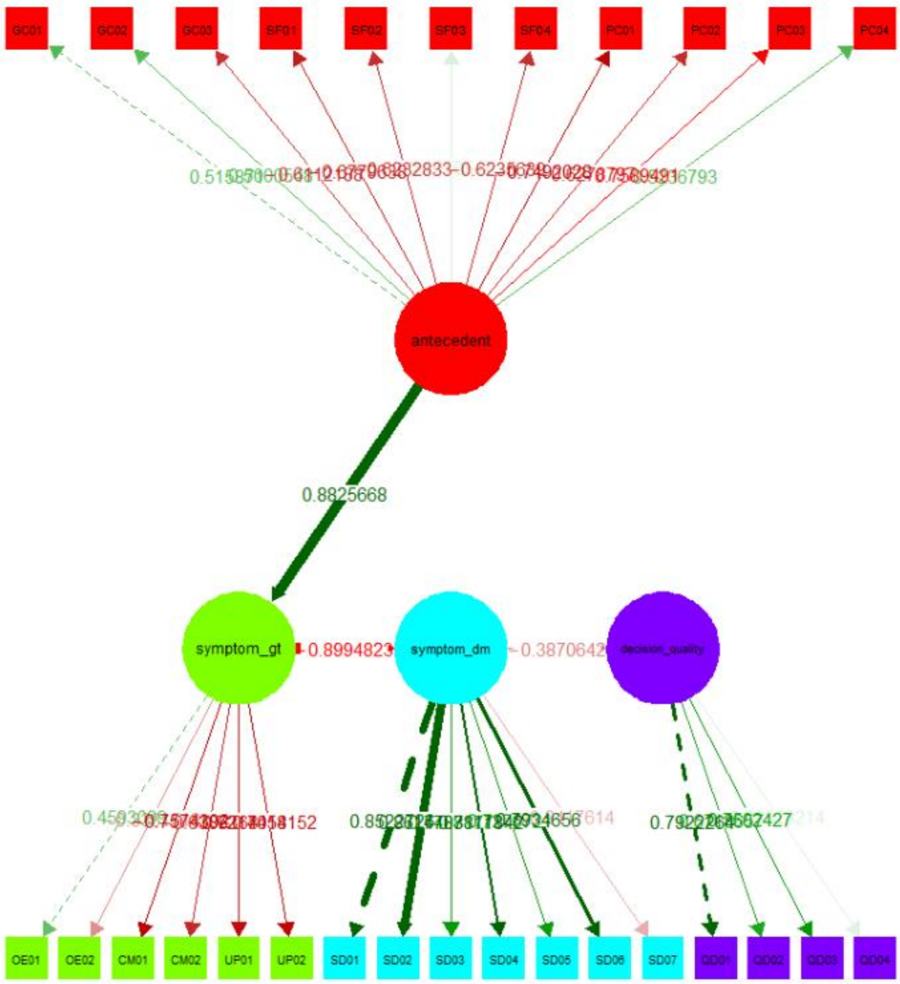
1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

Appendix 2: Descriptive statistics of survey dataset

Item	Observations	Average	Std. dev	Skewness	Kurtosis
GC01	251	3.384	0.804445	-0.38716	-0.02579
GC02	251	3.164	0.878745	-0.32637	0.024628
SF01	251	2.696	0.928997	0.338359	-0.35106
SF02	251	2.968	1.056143	0.105404	-0.60214
SF04	251	3.116	0.908761	0.189064	-0.45422
PC01	251	3.152	0.836478	-0.45877	0.022641
PC02	251	2.576	0.971597	0.326845	-0.43291
PC03	251	2.764	0.988033	0.16111	-0.5187
OE01	251	2.844	0.924708	0.407525	-0.41769
OE02	251	2.624	0.958278	0.318422	-0.57208
CM01	251	3.148	0.800412	-0.51032	0.112657
CM02	251	3.252	0.838635	-0.21549	-0.05138
UP01	251	2.964	0.827917	-0.14664	-0.42088

UP02	251	2.552	0.811127	0.444991	-0.14949
SD01	251	2.632	0.845836	0.301923	-0.45567
SD02	251	2.636	0.845199	0.330551	0.099389
SD03	251	2.752	0.851703	0.184772	-0.3128
SD04	251	2.632	0.855279	0.359433	-0.35187
SD05	251	2.828	0.863364	0.339979	-0.15604
SD06	251	2.816	0.867846	0.365916	-0.35955
SD07	251	2.732	0.847969	0.064827	-0.48216
QO01	251	2.844	0.871033	0.087982	-0.74779
QO02	251	2.744	0.830193	0.339587	-0.32925
QO03	251	3.116	0.715957	0.090374	0.296158

Appendix 3: Testing result of Janis' groupthink model



Appendix 4: Pseudo code of the agent-based model in chapter 3

(1) implementation.py

import modules

Generating data frames
experiment_type
performance
organizational_knowledge
agent_list

Define parameters
theta (insulation)
h_sup (leadership)
tau (lack of procedure)
max_iteration (outer loop)
experiment_iteration (inner loop)
agent_size
bit_of_knowledge

Declaration of agent class
class Agent
    number_of_agent
    homogeneity
    adjacency_matrix

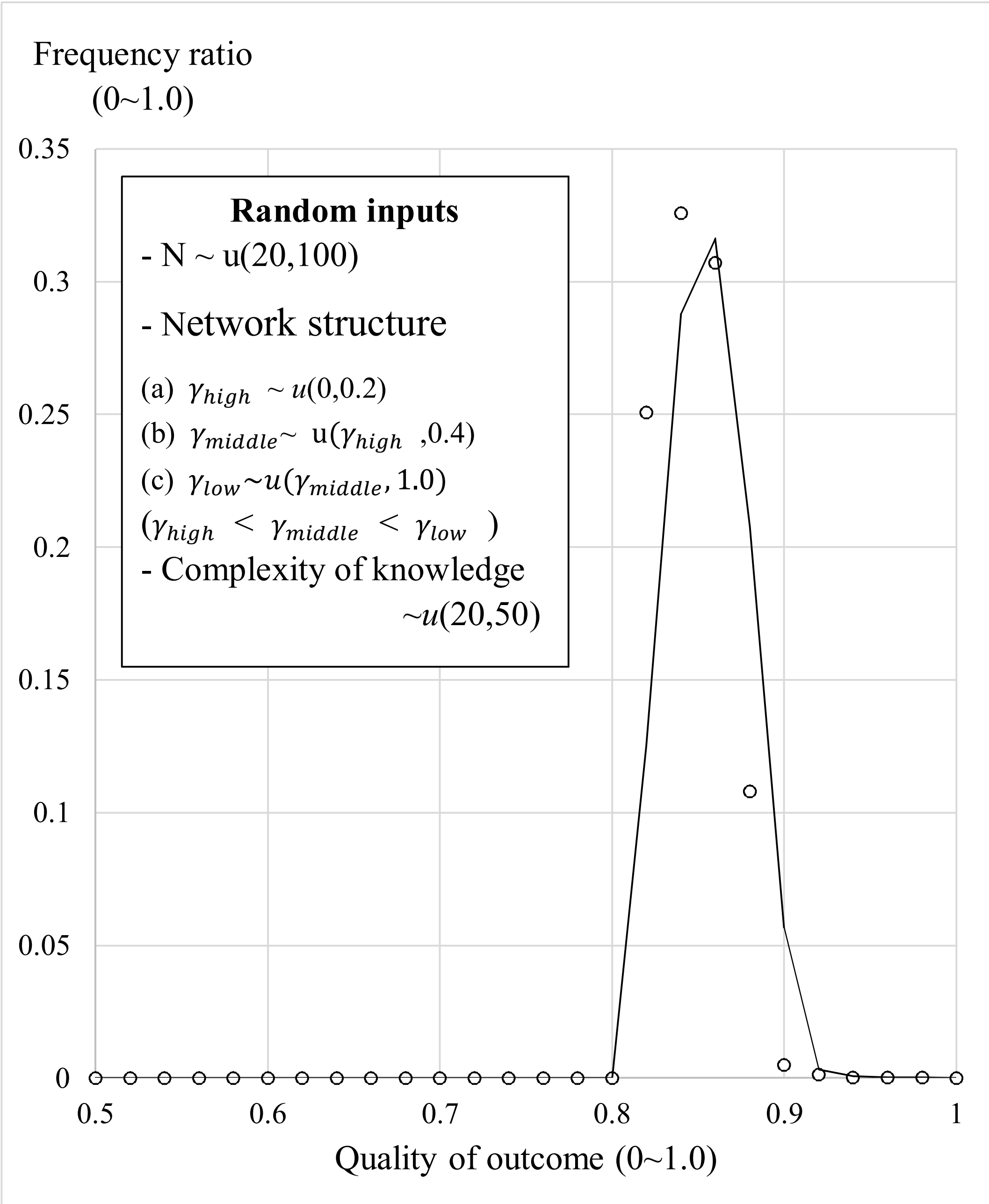
    def initialization_function():
id, mu (learning capability), mu_of_knowledge_distribution, stdev_of_knowledge distribution, learning_ratio, interaction_ratio, mutation, knowledge_landscape

    # Self functions of class
    def representation():

```
                return information_of_agent_class
        def basic_information():
                return information_of_each_agent
        def knowledge_information():
return information_of_organizational_knowledge, information_of_individual_knowledge
        def utility_maximization():
                return None

# Functions

def make_schema():
        return schema
def organizational_know():
        return organizational_knowledge
def make_agent():
        return the_list_of_agents
def performance_caculation():
        return performance
def learning():
        return None
def collaboration():
        return None

# Implementation

for i in range(0,max_iteration):
        for j in range(0, experiement_iteration):
make_schema()
                make_agent()
                organizational_knowledge()
                learning()
                performance_calculation()
```

```
                average_variance()

        performance = average_performance
        variance = average_variance

# Expression and save
# a) knowledge landscape
seaborn.displot()
plot.show()

# b) trend of organizational performance
pyplot.plot()
plot.show()

# c) trend of organizational diversity
pyplot.plot()
plot.show()

# d) save result dataset
performance_result_data.to_csv():
diversity_result_data.to_csv():
```

Appendix 5: Sensitivity test of groupthink ABM simulation



Appendix 6: Pseudo code of the agent-based model in chapter 4

implementation.py

```
import modules

# parameters
number of agent, max_iteration, seed

# generating agent class
class Agent:
        number_of_agent
        bit_of_knowledge
        optimal_solution
        organizational_knowledge
        organizational_performance
        adjacency_matrix

        def initialization():
                id, diversity, learning_capability
                def utility_function()
                def make_knowledge_distribution()
                def find_neighborhood_agent()
        def representation():
                return information_of_agent_class
        def show_info():
                return information_of_individual_agent


# define functions
def update_knowledge():
        return organizational_knowledge
def update_utility():
```

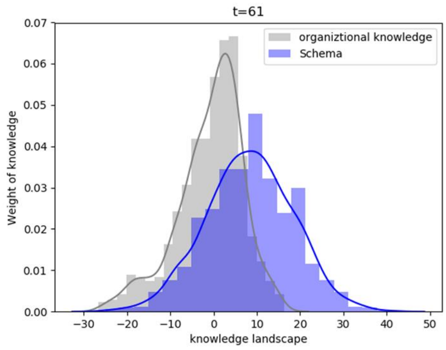
```
        return utility
def update_mu_sigma():
        return mu, sigma
def update_individual_performance():
        return performance
def update_network():
        return adjacency_matrix
def find_neighborhood():
        return None
def update_rank():
        return None
def average_utility():
        return average_utility
def knowledge_interaction():
        return None
def knowledge_interaction_delay():
        return None
def knowledge_mutation():
        return None
def normalize():
        return None
def plot_mu_sigma():
        return plot_of_mu_sigma
def knowledge_bias():
        return


# implementation


for i in range(0, max_iteration):
        # initialization
make_network ()
        find_neighborhood ()
```

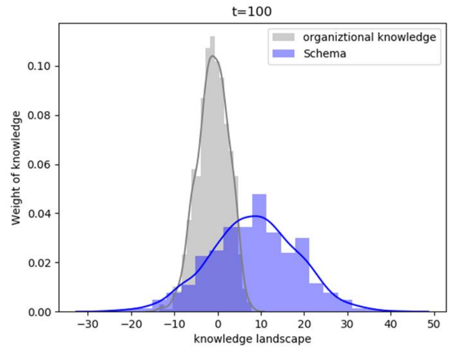
```
        update_organizational_knowledge ()
        update_organizational_performance ()
        update_individual_performance ()
        update_mu_sigma()
average_utility():
        update_rank()

# Save dataframe
result = performance, diversity, utility
result.to_csv()

# Save dataframe for MFA
result_mfa = performance, diversity, utility, learn_capability, learn_capability**2, organizational_diversity,
organizational_diversity**2
result_mfa.to_csv()
```

Appendix 7: Knowledge optimization processes of groupthink model

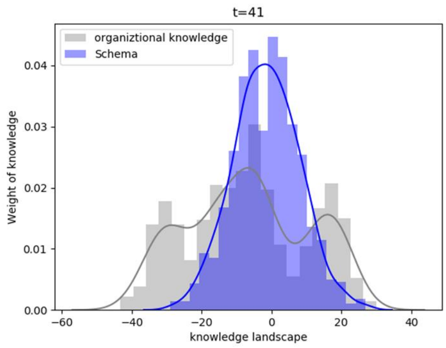
Middle of simulation　　　　　　　　End of simulation

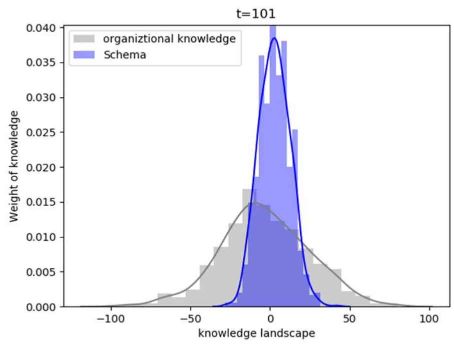
Group cohesiveness model



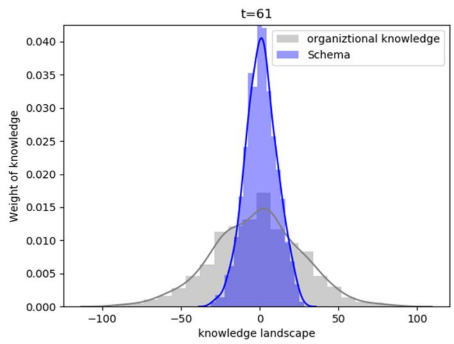


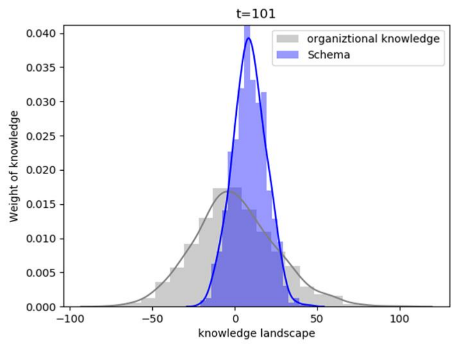
High insulation



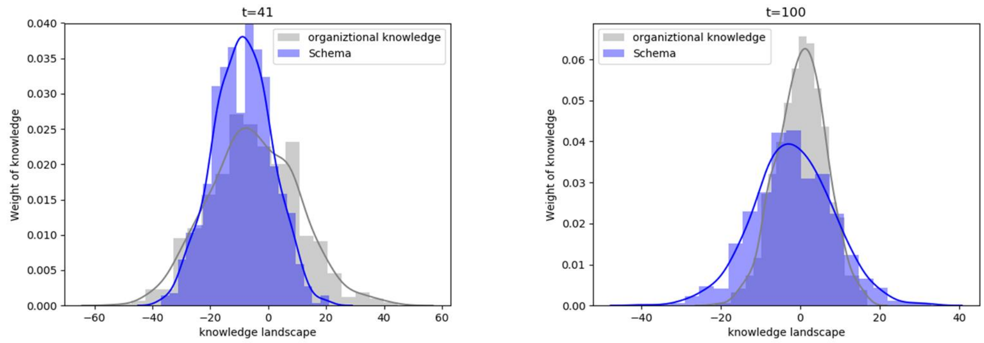


Directive leadership

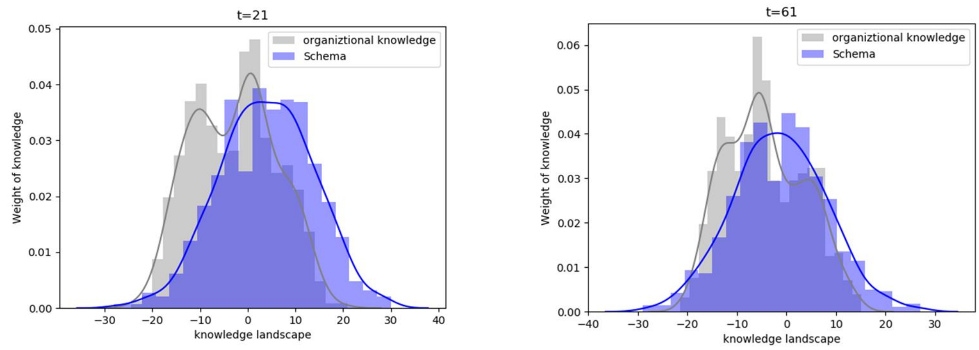




High homogeniety



Lack of norms



Appendix 8: Raw data of the quality of knowledge and average utility

	Raw data								Standardization							
	reference model		knowledge collision		delay		knowledge retrieval		reference model		knowledge collision		delay		knowledge retrieval	
	Uti	Perf	Uti	Perf	Uti	Perf	Uti	Perf	Uti	Perf	Uti	Perf	Uti	Perf	Uti	Perf
0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.08	73.00	2.27	78.00	2.16	78.00	2.58	72.00
1	1.06	1.08	1.05	1.03	1.04	1.00	1.11	1.21	2.20	79.00	2.39	80.00	2.23	78.00	2.87	87.00
2	1.12	1.19	1.12	1.14	1.09	1.09	1.17	1.35	2.33	87.00	2.54	89.00	2.36	85.00	3.03	97.00
3	1.15	1.25	1.15	1.17	1.11	1.13	1.21	1.43	2.40	91.00	2.60	91.00	2.40	88.00	3.12	103.00
4	1.16	1.26	1.15	1.18	1.12	1.12	1.22	1.44	2.41	92.00	2.61	92.00	2.41	87.00	3.14	104.00
5	1.16	1.26	1.19	1.24	1.14	1.17	1.23	1.47	2.41	92.00	2.69	97.00	2.45	91.00	3.17	106.00
6	1.18	1.33	1.21	1.28	1.16	1.23	1.23	1.47	2.46	97.00	2.73	100.00	2.51	96.00	3.18	106.00
7	1.19	1.34	1.21	1.28	1.17	1.24	1.23	1.47	2.47	98.00	2.74	100.00	2.52	97.00	3.18	106.00
8	1.18	1.33	1.22	1.29	1.18	1.27	1.23	1.44	2.47	97.00	2.77	101.00	2.54	99.00	3.17	104.00
9	1.19	1.36	1.22	1.29	1.18	1.28	1.22	1.43	2.48	99.00	2.77	101.00	2.55	100.00	3.16	103.00
10	1.19	1.33	1.23	1.29	1.20	1.32	1.23	1.44	2.47	97.00	2.79	101.00	2.59	103.00	3.18	104.00
11	1.19	1.33	1.24	1.32	1.21	1.33	1.23	1.44	2.47	97.00	2.82	103.00	2.62	104.00	3.18	104.00
12	1.20	1.36	1.23	1.28	1.21	1.33	1.23	1.44	2.49	99.00	2.79	100.00	2.61	104.00	3.18	104.00
13	1.20	1.36	1.24	1.27	1.22	1.35	1.22	1.43	2.49	99.00	2.80	99.00	2.63	105.00	3.17	103.00
14	1.20	1.36	1.24	1.27	1.22	1.33	1.22	1.43	2.49	99.00	2.81	99.00	2.64	104.00	3.17	103.00

15	1.20	1.36	1.25	1.28	1.23	1.36	1.23	1.44	2.49	99.00	2.83	100.00	2.65	106.00	3.17	104.00
16	1.20	1.36	1.25	1.27	1.23	1.35	1.23	1.44	2.49	99.00	2.83	99.00	2.65	105.00	3.18	104.00
17	1.20	1.36	1.25	1.27	1.23	1.35	1.24	1.47	2.49	99.00	2.83	99.00	2.65	105.00	3.20	106.00
18	1.20	1.36	1.25	1.26	1.23	1.35	1.24	1.47	2.49	99.00	2.82	98.00	2.65	105.00	3.20	106.00
19	1.20	1.36	1.25	1.26	1.23	1.35	1.24	1.47	2.49	99.00	2.83	98.00	2.65	105.00	3.20	106.00
20	1.20	1.36	1.26	1.27	1.23	1.36	1.24	1.47	2.49	99.00	2.85	99.00	2.66	106.00	3.20	106.00
21	1.20	1.36	1.26	1.26	1.24	1.37	1.24	1.47	2.49	99.00	2.85	98.00	2.67	107.00	3.20	106.00
22	1.20	1.36	1.26	1.27	1.24	1.37	1.24	1.47	2.49	99.00	2.86	99.00	2.67	107.00	3.21	106.00
23	1.20	1.36	1.27	1.27	1.24	1.37	1.25	1.50	2.49	99.00	2.87	99.00	2.68	107.00	3.23	108.00
24	1.20	1.36	1.26	1.26	1.24	1.37	1.25	1.50	2.49	99.00	2.86	98.00	2.68	107.00	3.23	108.00
25	1.20	1.36	1.27	1.27	1.24	1.37	1.25	1.50	2.49	99.00	2.87	99.00	2.67	107.00	3.23	108.00
26	1.20	1.36	1.26	1.24	1.24	1.37	1.25	1.50	2.49	99.00	2.86	97.00	2.67	107.00	3.23	108.00
27	1.20	1.36	1.28	1.28	1.24	1.37	1.25	1.50	2.49	99.00	2.89	100.00	2.67	107.00	3.23	108.00
28	1.20	1.36	1.27	1.27	1.24	1.37	1.25	1.51	2.49	99.00	2.89	99.00	2.67	107.00	3.24	109.00
29	1.20	1.36	1.27	1.27	1.24	1.37	1.25	1.51	2.49	99.00	2.88	99.00	2.67	107.00	3.24	109.00
30	1.20	1.36	1.28	1.28	1.24	1.37	1.25	1.51	2.49	99.00	2.91	100.00	2.67	107.00	3.24	109.00
31	1.20	1.36	1.28	1.27	1.24	1.37	1.25	1.51	2.49	99.00	2.89	99.00	2.67	107.00	3.24	109.00
32	1.20	1.36	1.28	1.27	1.24	1.37	1.26	1.51	2.49	99.00	2.89	99.00	2.67	107.00	3.25	109.00
33	1.20	1.36	1.28	1.28	1.24	1.37	1.26	1.51	2.49	99.00	2.90	100.00	2.67	107.00	3.25	109.00

34	1.20	1.36	1.28	1.28	1.24	1.37	1.26	1.51	2.49	99.00	2.90	100.00	2.67	107.00	3.25	109.00
35	1.20	1.36	1.29	1.29	1.24	1.37	1.26	1.51	2.49	99.00	2.92	101.00	2.67	107.00	3.25	109.00
36	1.20	1.36	1.29	1.29	1.24	1.38	1.26	1.51	2.49	99.00	2.92	101.00	2.68	108.00	3.25	109.00
37	1.20	1.36	1.29	1.29	1.24	1.38	1.26	1.51	2.49	99.00	2.92	101.00	2.68	108.00	3.25	109.00
38	1.20	1.36	1.29	1.29	1.24	1.38	1.26	1.51	2.49	99.00	2.93	101.00	2.68	108.00	3.25	109.00
39	1.20	1.36	1.29	1.27	1.24	1.38	1.26	1.51	2.49	99.00	2.91	99.00	2.68	108.00	3.25	109.00
40	1.20	1.36	1.29	1.27	1.24	1.38	1.26	1.53	2.49	99.00	2.92	99.00	2.68	108.00	3.26	110.00
41	1.20	1.36	1.29	1.29	1.24	1.38	1.27	1.54	2.49	99.00	2.93	101.00	2.68	108.00	3.27	111.00
42	1.20	1.36	1.29	1.29	1.24	1.38	1.27	1.54	2.49	99.00	2.94	101.00	2.68	108.00	3.27	111.00
43	1.20	1.36	1.29	1.28	1.24	1.38	1.27	1.54	2.49	99.00	2.93	100.00	2.68	108.00	3.27	111.00
44	1.20	1.36	1.31	1.31	1.24	1.38	1.27	1.54	2.49	99.00	2.96	102.00	2.68	108.00	3.27	111.00
45	1.20	1.36	1.30	1.31	1.24	1.38	1.27	1.54	2.49	99.00	2.95	102.00	2.68	108.00	3.27	111.00
46	1.20	1.36	1.31	1.31	1.24	1.38	1.27	1.54	2.49	99.00	2.96	102.00	2.68	108.00	3.27	111.00
47	1.20	1.36	1.30	1.31	1.24	1.38	1.27	1.54	2.49	99.00	2.96	102.00	2.68	108.00	3.27	111.00
48	1.20	1.36	1.30	1.29	1.24	1.38	1.27	1.54	2.49	99.00	2.95	101.00	2.68	108.00	3.27	111.00
49	1.20	1.36	1.31	1.32	1.24	1.38	1.27	1.54	2.49	99.00	2.97	103.00	2.68	108.00	3.27	111.00
50	1.20	1.36	1.31	1.32	1.24	1.38	1.27	1.54	2.49	99.00	2.97	103.00	2.68	108.00	3.27	111.00
51	1.20	1.36	1.31	1.32	1.24	1.38	1.27	1.54	2.49	99.00	2.97	103.00	2.68	108.00	3.28	111.00
52	1.20	1.36	1.31	1.33	1.24	1.38	1.27	1.51	2.49	99.00	2.98	104.00	2.68	108.00	3.28	109.00

53	1.20	1.36	1.32	1.35	1.24	1.38	1.28	1.53	2.49	99.00	2.99	105.00	2.68	108.00	3.31	110.00
54	1.20	1.36	1.32	1.35	1.24	1.38	1.28	1.50	2.49	99.00	2.99	105.00	2.68	108.00	3.30	108.00
55	1.20	1.36	1.32	1.36	1.24	1.38	1.27	1.47	2.49	99.00	3.00	106.00	2.68	108.00	3.28	106.00
56	1.20	1.36	1.32	1.35	1.24	1.38	1.27	1.47	2.49	99.00	3.00	105.00	2.68	108.00	3.28	106.00
57	1.20	1.36	1.33	1.35	1.24	1.38	1.26	1.44	2.49	99.00	3.00	105.00	2.68	108.00	3.25	104.00
58	1.20	1.36	1.34	1.38	1.24	1.38	1.26	1.46	2.49	99.00	3.03	108.00	2.68	108.00	3.27	105.00
59	1.20	1.36	1.34	1.37	1.24	1.38	1.25	1.43	2.49	99.00	3.03	107.00	2.68	108.00	3.24	103.00
60	1.20	1.36	1.34	1.37	1.24	1.38	1.24	1.39	2.49	99.00	3.03	107.00	2.68	108.00	3.21	100.00
61	1.20	1.36	1.35	1.38	1.24	1.38	1.25	1.39	2.49	99.00	3.05	108.00	2.68	108.00	3.22	100.00
62	1.20	1.36	1.34	1.37	1.24	1.38	1.25	1.39	2.49	99.00	3.04	107.00	2.68	108.00	3.22	100.00
63	1.20	1.36	1.35	1.40	1.24	1.38	1.25	1.39	2.49	99.00	3.06	109.00	2.68	108.00	3.22	100.00
64	1.20	1.36	1.35	1.40	1.24	1.38	1.25	1.39	2.49	99.00	3.07	109.00	2.68	108.00	3.22	100.00
65	1.20	1.36	1.36	1.40	1.24	1.38	1.24	1.36	2.49	99.00	3.08	109.00	2.68	108.00	3.20	98.00
66	1.20	1.36	1.37	1.42	1.24	1.38	1.23	1.35	2.49	99.00	3.10	111.00	2.68	108.00	3.18	97.00
67	1.20	1.36	1.37	1.42	1.24	1.38	1.22	1.32	2.49	99.00	3.10	111.00	2.68	108.00	3.15	95.00
68	1.20	1.36	1.37	1.42	1.24	1.38	1.21	1.31	2.49	99.00	3.10	111.00	2.68	108.00	3.14	94.00
69	1.20	1.36	1.38	1.46	1.24	1.38	1.21	1.29	2.49	99.00	3.14	114.00	2.68	108.00	3.13	93.00
70	1.20	1.36	1.39	1.47	1.24	1.38	1.21	1.29	2.49	99.00	3.15	115.00	2.68	108.00	3.13	93.00
71	1.20	1.36	1.39	1.49	1.24	1.38	1.21	1.29	2.49	99.00	3.16	116.00	2.68	108.00	3.13	93.00

72	1.20	1.36	1.40	1.50	1.24	1.38	1.20	1.28	2.49	99.00	3.17	117.00	2.68	108.00	3.11	92.00
73	1.20	1.36	1.41	1.53	1.24	1.38	1.20	1.28	2.49	99.00	3.19	119.00	2.68	108.00	3.11	92.00
74	1.20	1.36	1.41	1.54	1.24	1.38	1.20	1.26	2.49	99.00	3.20	120.00	2.68	108.00	3.09	91.00
75	1.20	1.36	1.41	1.54	1.24	1.38	1.19	1.25	2.49	99.00	3.21	120.00	2.68	108.00	3.08	90.00
76	1.20	1.36	1.42	1.55	1.24	1.38	1.18	1.24	2.49	99.00	3.22	121.00	2.68	108.00	3.05	89.00
77	1.20	1.36	1.43	1.58	1.24	1.38	1.17	1.21	2.49	99.00	3.24	123.00	2.68	108.00	3.02	87.00
78	1.20	1.36	1.43	1.58	1.24	1.38	1.17	1.21	2.49	99.00	3.25	123.00	2.68	108.00	3.02	87.00
79	1.20	1.36	1.44	1.59	1.24	1.38	1.17	1.19	2.49	99.00	3.26	124.00	2.68	108.00	3.02	86.00
80	1.20	1.36	1.45	1.62	1.24	1.38	1.17	1.19	2.49	99.00	3.28	126.00	2.68	108.00	3.02	86.00
81	1.20	1.36	1.46	1.63	1.24	1.38	1.16	1.19	2.49	99.00	3.30	127.00	2.68	108.00	3.01	86.00
82	1.20	1.36	1.46	1.63	1.24	1.38	1.17	1.19	2.49	99.00	3.31	127.00	2.68	108.00	3.01	86.00
83	1.20	1.36	1.46	1.64	1.24	1.38	1.16	1.19	2.49	99.00	3.31	128.00	2.68	108.00	3.01	86.00
84	1.20	1.36	1.46	1.65	1.24	1.38	1.17	1.21	2.49	99.00	3.32	129.00	2.68	108.00	3.02	87.00
85	1.20	1.36	1.47	1.65	1.24	1.38	1.16	1.19	2.49	99.00	3.32	129.00	2.68	108.00	3.01	86.00
86	1.20	1.36	1.47	1.67	1.24	1.38	1.17	1.21	2.49	99.00	3.33	130.00	2.68	108.00	3.03	87.00
87	1.20	1.36	1.48	1.68	1.24	1.38	1.17	1.21	2.49	99.00	3.35	131.00	2.68	108.00	3.03	87.00
88	1.20	1.36	1.48	1.69	1.24	1.38	1.17	1.19	2.49	99.00	3.36	132.00	2.68	108.00	3.03	86.00
89	1.20	1.36	1.49	1.71	1.24	1.38	1.17	1.18	2.49	99.00	3.37	133.00	2.68	108.00	3.02	85.00
90	1.20	1.36	1.50	1.73	1.24	1.38	1.17	1.18	2.49	99.00	3.39	135.00	2.68	108.00	3.02	85.00

91	1.20	1.36	1.50	1.74	1.24	1.38	1.16	1.17	2.49	99.00	3.41	136.00	2.68	108.00	3.01	84.00
92	1.20	1.36	1.51	1.76	1.24	1.38	1.16	1.17	2.49	99.00	3.42	137.00	2.68	108.00	3.01	84.00
93	1.20	1.36	1.52	1.77	1.24	1.38	1.15	1.14	2.49	99.00	3.44	138.00	2.68	108.00	2.97	82.00
94	1.20	1.36	1.53	1.79	1.24	1.38	1.15	1.15	2.49	99.00	3.46	140.00	2.68	108.00	2.98	83.00
95	1.20	1.36	1.53	1.79	1.24	1.38	1.15	1.14	2.49	99.00	3.46	140.00	2.68	108.00	2.97	82.00
96	1.20	1.36	1.53	1.79	1.24	1.38	1.14	1.13	2.49	99.00	3.47	140.00	2.68	108.00	2.96	81.00
97	1.20	1.36	1.53	1.79	1.24	1.38	1.14	1.13	2.49	99.00	3.47	140.00	2.68	108.00	2.96	81.00
98	1.20	1.36	1.53	1.79	1.24	1.38	1.13	1.10	2.49	99.00	3.48	140.00	2.68	108.00	2.93	79.00
99	1.20	1.36	1.54	1.82	1.24	1.38	1.13	1.10	2.49	99.00	3.50	142.00	2.68	108.00	2.93	79.00
100	1.20	1.36	1.54	1.82	1.24	1.38	1.13	1.10	2.49	99.00	3.50	142.00	2.68	108.00	2.93	79.00

Appendix 9: Questionnaire of chapter 5

PART1: Demographic information

P1. What is the age of the respondent?

1	2	3	4	5
20~30s	30~40s	40~50s	50~60s	Over 60s

P2. What is the gender of the respondent?

1	2
Male	Female

P3. What is the final education of the respondent?

1	2	3	4
High school	University	Master	Ph.D

P4. What kind of organization are you belonged to?

1	2	3
Firm	Public organization	R&D Institute

P5. What kind of task are you doing?

1	2	3	4	5
Administration	R&D	Marketing	Distribution	Etc

P6. What is the position of the respondent?

1	2	3	4	5
Part time	Employee	Manager	Board	Etc

P7. What is the size of your entire organization?

1	2	3	4	5
Under 10	10~50	50~150	150 ~ 500	Over 500

P7. What is the size of your organization?

1	2	3	4	5
Under 10	10~50	50~150	Over 150	Over 500

PART2: Symptoms of groupthink

GS_01. The organization where I belong does not fully investigate the alternatives which is available

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_02. The organization where I belong does not consider enough the goal of organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_03. The organization where I belong does not evaluate or analyze the decision making which is already determined.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_04. The excluded alternatives do not be considered after that.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_05. Sufficient data and information are not prepared during examining the alternatives.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_06. Collected data and information considered in the examination process are biased to the certain point.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

GS_07. The organization where I belong does not consider the contingency plan (plan B).

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART3: Collective intelligence

(1) Average intelligence

AI_01. What is the level of understanding toward the tasks of your colleague?

1	2	3	4	5
very low	low	moderate	high	very high

AI_02. What is the average education level of your organization?

1	2	3	4	5

Middle school	High school	University	Master	Ph.D

AI_03. What is the average length of service?

1	2	3	4	5
Under 6 month	6month ~ 2 year	2~5 year	5~10 year	Over 10 year

(2) ToM score

TS_01. I am easy to empathize with the emotion of other people.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

TS_02. It is easy for me to read another's thought or emotion.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

TS_03. I sensitively react to the another's opinion.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

TS_04. I concern about the reactions of others.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(3) Organizational diversity

OD_01. What is the ratio of female in your organization?

1	2	3	4	5	6
Under 10%	10%~ 30%	30%~50%	50%~70%	70%~90%	Over 90%

OD_02. The members of my organization have diverse knowledge background.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

(3) Organization structure

OS_01. It is easy to express my thought during the discussion.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OS_02. All ideas are considered equally regardless who raise the idea.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OS_03. The organization where I belong provide equal opportunity to express own idea.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART4: The use of BDA

※ BDA: 'Big data analytics' refers to the process of collecting and refining large amounts of data and information to build data (database) for the purpose of the organization and extract significant knowledge in various ways (statistical estimates, machine learning, deep learning, etc.).

BU_01. It is easy for my organization to utilize BDA to achieve the goal of the organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

BU_02. The use of BDA is effective method to achieve the goal of the organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

BU_03. My organization trust the knowledge that derived from BDA.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

BU_04. The use of BDA will fulfil the expectation of my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

BU_05. My current organization is difficult to deal with problems effectively without the use of the BDA

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

PART5: The use of Online platform

※ Online platform: Online platforms are platforms built in virtual cyberspace to share people's thoughts, knowledge, and emotions, including Google, Yahoo, Wikipedia, and GitHub.

OU_01. It is easy for my organization to utilize online platform to achieve the goal of the organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OU_02. The use of online platform is effective method to achieve the goal of the organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OU_03. My organization trust the knowledge that derived from online platform.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OU_04. The use of BDA will fulfil the expectation of my organization.

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

OU_05. My current organization is difficult to deal with problems effectively without the use of online platform

1	2	3	4	5
Strongly disagree	disagree	neutral	agree	strongly agree

Appendix 10: Derivation of the conceptual meaning for knowledge distribution representation

In this study, I adopted Langevine equation to explains the change of knowledge distributions.

$$x(t) - x(0) = \int_0^t dt' a[x(t'), t'] + \int_0^t dW(t') b[x(t'), t']$$

Assume that the initial time is an arbitrary point (t_0), deviation of location of x is,

$$\Delta x_{t,0} = x(t) - x(0) = x(t_0) + \int_{t_0}^t dt' a[x(t'), t'] + \int_{t_0}^t dW(t') b[x(t'), t']$$

also, applying Taylor expansion to this equation that location x is a random variable($f(x(t))$ which has probability density function (f), then the equation can be derived as,

$$\frac{df(x(t))}{dt} = f[x(t) + \mathrm{d}x(t)] - f[x(t)] = f'[x(t)]dx(t) + \frac{1}{2}f''[x(t)]dx(t)^2 + \cdots$$

In here, deviation of x can be substitute $dx(t)$, and then the equation is,

$$\frac{df(x(t))}{dt} = f'[x(t)]\left[x(t_0) + \int_{t'}^t dt' a[x(t'), t'] + \int_{t'}^t dW(t') b[x(t'), t']\right]$$
$$+ \frac{1}{2}f''[x(t)]\left[\int_{t_0}^t b[x(t'), t']\right]^2 dW(t')^2 + \cdots$$

Since $\mathrm{dW(t)}^{N+2} = 0$ $(N > 0)$ by the definition of Weiner process,

$$\frac{df(x(t))}{dt} = f'[x(t)]\left[x(t_0) + \int_{t'}^t dt' a[x(t'), t'] + \int_{t'}^t dW(t') b[x(t'), t']\right]$$
$$+ \frac{1}{2}f''[x(t)]\left[\int_{t_0}^t b[x(t'), t']\right]^2 dW(t')^2$$

In the classical physics, the first order of location means velocity and the second order referst to the acceleration. For the conveniece, let's express each term as $\mathrm{A}(x,t), \mathrm{B}(x,t)$.

$$df(x(t)) = dW(t)\mathrm{A}(x,t) + \frac{1}{2}dW(t)^2\mathrm{B}(x,t)^2$$

To identify the meaning of each terms, I calculate the expectation of this equation like below.

$$E[df(x(t))] = \mathrm{E}[dW(t)\mathrm{A}(x,t)] + E[\frac{1}{2}dW(t)^2\mathrm{B}(x,t)^2]$$

Since Wiener process ($dW(t)^2$) is independent from the other trems ($\mathrm{A}(x,t), \mathrm{B}(x,t)^2$),

$$E\big[df\big(x(t)\big)\big] = \mathrm{E}[dW(t)\mathrm{A}(x,t)] + \frac{1}{2}E[dW(t)^2]E[\mathrm{B}(x,t)^2]$$

$$= \mathrm{E}[dW(t)\mathrm{A}(x,t)] + \frac{1}{2} \times 0 \times E[\mathrm{B}(x,t)^2] = \mathrm{E}[dW(t)] \times \mathrm{E}[\mathrm{A}(x,t)]$$

$$\therefore E\big[df\big(x(t)\big)\big] = \mathrm{E}[dW(t)] \times \mathrm{E}[\mathrm{A}(x,t)]$$

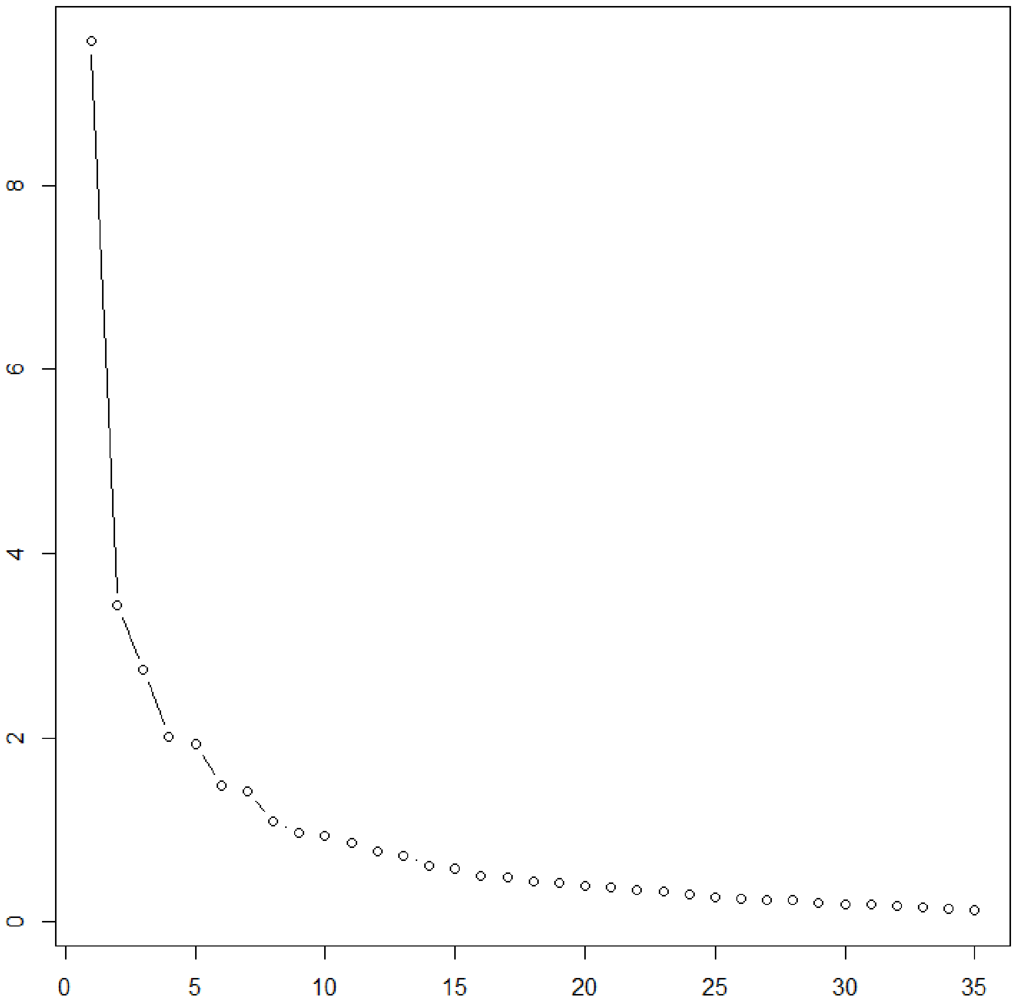
Thus, the term $\mathrm{A}(x,t)$ refers to the expectation of deviation of location at time *t*. In other words, $\mathrm{A}(x,t)$ shows the direction and amout of drift of location *x*. Naturally, $\mathrm{B}(x,t)^2$ becomes the noise term randomly disturbing the location of *x*.

Appendix 11: Result comparison of linear programing and quadratic programing in meta-frontier analysis

	Linear Programing			Quadratic Programing		
	TE	TGR	TGR*TE=TE*	TE	TGR	TGR*TE=TE*
1	8.02E-01	0.133071	0.1067	8.02E-01	0.011837	0.0095
2	9.89E-01	0.000602	0.0006	9.89E-01	0.000119	0.0001
3	9.91E-01	0.0385	0.0382	9.91E-01	0.005992	0.0059
4	9.94E-01	0.129531	0.1287	9.94E-01	0.014222	0.0141
5	9.91E-01	0.158192	0.1568	9.91E-01	0.016383	0.0162
6	9.94E-01	0.021015	0.0209	9.94E-01	0.003056	0.0030
7	9.90E-01	0.189159	0.1873	9.90E-01	0.007867	0.0078
8	9.89E-01	0.067311	0.0665	9.89E-01	0.007036	0.0070
9	9.94E-01	0.142187	0.1413	9.94E-01	0.006438	0.0064
…						
7997	9.94E-01	0.618833	0.6149	9.94E-01	0.052193	0.0519
7998	9.95E-01	0.946498	0.9422	9.95E-01	0.100336	0.0999
7999	9.93E-01	0.604594	0.6004	9.93E-01	0.060566	0.0601
8000	9.95E-01	0.768182	0.7646	9.95E-01	0.157954	0.1572

Appendix 12: Principal component analysis (PCA)

(1) Number of eigenvector



(2) Factor loadings

Components (proportion value)	Groupthink symptoms	Use of online platforms	Use of Big data analytics	Task complexity	Organizational equality	Collective intelligence (ToM)	Individual capability	Organizational diversity
	16%	12%	9%	8%	7%	6%	5%	4%
GT1	0.81	-0.12	-0.14	-0.01	-0.14	-0.02	-0.05	-0.03
GT2	0.83	-0.13	-0.12	-0.07	-0.07	0.07	-0.05	0.05
GT3	0.84	-0.09	-0.17	0.01	-0.15	0.01	-0.05	0
GT4	0.79	-0.07	-0.07	-0.11	-0.09	0.03	0.02	-0.05

GT5	0.86	-0.17	-0.11	-0.07	-0.04	0.03	-0.05	-0.02
GT6	0.81	-0.08	-0.13	-0.11	-0.21	0.05	0	-0.06
GT7	0.82	-0.16	-0.15	-0.09	0.02	0.04	0.04	0
Indcap1	-0.05	0.11	0.03	-0.1	-0.24	0.05	0.61	0.23
Indcap2	0.04	0.13	0.02	0.11	0.14	0.12	0.81	0.15
Indcap3	-0.07	-0.02	0.08	0.15	0.21	0.2	0.8	-0.08
CI1	-0.11	0.02	0.21	0.26	0.04	0.47	0.2	0.03
CI2	-0.05	0.21	0.14	0.03	-0.04	0.58	0.19	-0.03
CI3	0.1	-0.07	0.02	-0.01	-0.04	0.87	0.01	0.07
CI4	0.15	-0.06	-0.04	0.01	0	0.82	0.04	0.08
Orgdiv1	0.13	0.09	-0.05	-0.09	0.41	0.28	0.01	0.67
Orgdiv2	-0.32	0.32	0.05	0.37	0.2	0.19	0.09	0.51
Orgeq1	-0.29	0.17	0.17	0.1	0.75	-0.13	0.07	0.13
Orgeq2	-0.32	0.25	0.11	0.07	0.79	-0.05	0.07	0.12
Orgeq3	-0.37	0.31	0.15	-0.01	0.71	-0.04	0.04	0.06
TC1	-0.02	0.04	0.07	0.72	-0.03	0	-0.04	-0.02
TC2	-0.07	0.1	0.1	0.72	-0.05	0.11	-0.09	0.04
TC3	-0.12	0.06	0.17	0.73	0.16	0.02	0.19	0.06
TC4	-0.09	-0.01	0.02	0.79	-0.01	-0.02	0.12	0.18
useBDA1	-0.35	0.21	0.69	0.05	0.18	0.11	-0.01	0.02
useBDA2	-0.24	0.26	0.71	0.17	-0.06	0.06	0.15	-0.03
useBDA3	-0.26	0.3	0.77	0.06	0.05	0.04	0.04	0
useBDA4	-0.23	0.27	0.78	0.02	0.1	0.03	0.05	0.02
useBDA5	0.02	0.08	0.79	0.18	0.09	0.05	-0.01	0.05
useOP1	-0.21	0.81	0.11	0.05	0.14	0.01	0.06	0.05
useOP2	-0.14	0.85	0.21	0.08	0.07	0	0.09	-0.02
useOP3	-0.07	0.81	0.23	0	0.14	-0.04	0.06	-0.05
useOP4	-0.19	0.83	0.18	0.13	0.11	0.05	0.02	0.04
useOP5	-0.13	0.81	0.25	0.03	0.17	0.07	0.03	-0.03

Abstract (Korean)

지식은 인류의 진보를 위한 중요한 원천 중 하나이다. 지식의 중요성 동안 다양한 분야에서, 시간이 지나면서 독립 전문가들, 시스템 및 연구 결과는 오로지 지식을 다루는 등장했다 강조되고 있다. 최근 기술의 급속한 발전은 우리 사회에 더 많은 양과 질 높은 지식을 필요로 했고, 그 지식은 경쟁 자체가 되었다. 초기의 지식 창출 과정은 개인 또는 소수의 전문가 집단의 역할을 강조했다. 특히 전문가들의 훌륭한 개인이 작은 규모에 의해 지식의 창출, 지식의 생산에 가장 기여한다고 여겨져 왔다. 그러나, 온라인상에서 공간 정보 통신 기술 출현 및 빅 데이터의 사용은 전례 없이 인간의 지식 생산 과정을 바꾸기 시작했다.

지식의 생산 개인 능력에 따라 점차 새로운 기술과 많은 사람들에 의해 대체되기 시작했다. 새로운 기술과 조직 협력의 조합은 조직적 의사 결정의 주요 동인으로 활용되는 새로운 지식 시스템인 집단 지성이라고 불리는 방안을 제안되기 시작했다. 이러한 방식은 현대 사회 조직들의 지식 창출의 중요한 축을 담당하고 있다. 위키피디아는 온라인 플랫폼 이 집단 지성을 이용하는 가장 성공적인 분야이다. 이 플랫폼은 무작위의 사람들이 참여하며, 단지 지식과 수정 저장될 수 있는 인터페이스를 준다. 세계적으로 가장 큰 지식 플랫폼인 위키피디아의 성공은 군중 속에서 지식 전문가 집단의 개입 없이 통합된 상호작용으로써 이지식 생태계의 높은 수준을 만든다는 것을 증명했으며, 또한 지식 창출의 주 동력이 재능 있는 개인들 에서 조직으로 옮겨 가고 있다는

걸 증명하였다.

하지만 집단 지성의 일부 한계 가지고 있었다. 첫째, 집단 지성은 일반적으로 높은 수준의 분권화와 수평 계층 구조를 갖기 때문에, 개별 지식의 통합 어렵다. 단순한 의견 통합 방식은 집단지성의 상승효과를 방해하고 집단사고로 인한 결함 있는 지식 생산을 야기할 수 있기 때문에, 집단지성을 위한 새로운 지식 통합 방식이 요구된다. 또 다른 문제는 지식의 평가에 있다. 특히 지식에 대한 평가는 문제가 하나의 해결책을 갖지 않을 때 더욱 중요해진다. 이것이 새로운 지식 평가 방식이 필요한 이유이다. 또한 지식 생산을 성공적으로 달성하기 위해서는 다양한 조건들이 충족되어야 한다. 그 때문에 집단 지능에 관한 선행연구의 대부분은 성공적인 집단 지능의 조건에 초점을 맞추고 있다.

만약 집단지성의 조건이 충족되지 않는다면? 이에 대한 해답은 집단지능 관점이 채택되기 전에 도입된 집단 사고의 개념에 있었다. 집단 사고는 조직의 합의를 이루기 위해 대안에 대한 비판, 평가 및 고려를 간과하는 집단적 경향으로 정의된다. 집단 사고는 집단지성과는 달리 조직적 의사결정 실패의 원인으로 지적되어 왔다. 그래서 관련 연구는 조직적인 실패를 막기 위해 집단 사고의 원인을 규명하고 해결할 해결책을 찾는 데 초점을 맞추고 있다. 그러나 집단지성과 집단적 사고는 모두 조직적 지식 창출이나 의사결정의 과정에서 자연스럽게 발생하는 현상이다. 하지만 집단사고의 원인을 찾는 것이 진정한 해결책이 될 수 있는지에 대해서는 의문이 존재한다.

집단 지성과 집단사고 현상은 조직의 지식창출 또는 의사결정 과정에서 발

생한다. 그들의 결과물과 무관하게, 조직은 그들의 목표달성을 위하여 꾸준히 지식창출 행위를 수행해야 한다. 그러나 문제는 결과에 대한 평가가 이루어지기 이전에는 그들의 조직이 현재 집단사고와 집단지성 중 어떤 상황에 있는지를 알아내기가 어렵다는 점이다. 수 많은 연구들이 조직 지식 창출과 관리를 효과적으로 하기 위하여 이론과 가설들을 제시하여 왔다. 그러나 불행히도 집단사고와 집단지성의 전환의 관점에서 이루어진 연구는 거의 없었다.

이 논문의 목적은 집단 사고와 집단 지성이라는 두 가지 개념을 바탕으로 조직 지식 창출의 방법을 이해하는 것이다. 나의 연구목표를 완성하기 위해 세 가지 작은 주제가 제기되었다. 첫째, 우리는 집단 실패의 주요 원인 중 하나로 가장 널리 사용되어 온 집단 사고 현상을 고려해야 한다. 둘째, 집단 사고와 집단지성을 연결하는 다리는 조직 지식 창조를 강화하는 요인을 찾아내기 위해 세워져야 한다. 셋째, 몇 가지 전략적인 측면이 필요하다. 자기 조직화와 사회 기술적 관점에서 본 논문은 조직 지식 창출을 위한 효과적인 전략을 제안한다. 제3장의 첫 번째 연구는 '조직에서 집단 사고를 없앨 수 있을까?'라는 첫 번째 주제에 대한 답을 주려고 노력했다. 제3장에서 제안된 집단 사고의 다른 관점들에 근거하여 집단 사고의 집단지성으로 전환하는 요인을 도출한다. 제4장에서는 전환 요인의 효과와 이를 이용한 효율적인 전략에 대해 논한다. 제4장에서의 결과들은 '집단 사고와 집단지능 사이에 어떤 연관성이 있는가?'라는 질문에 대한 답을 줄 수 있다. 제5장 본 논문의 마지막 연구에서는 빅데이터 분석, 온라인 플랫폼 등의 기술 활용을 위한 효과적인 전략을 제안하는 것을 목표로 한다. 각 연구의 자세한 내용은 다음과 같다,

첫 번째 연구 "Is groupthink really inevitable?: based on self-organization aspect"는 집단 사고의 긴급한 메커니즘에 관한 것이다. 이 연구는 두 가지 주제를 상세히 다루고 있다. 첫번째는 Janis의 집단 사고 모델을 가장 잘 알려진 것으로 검증하는 것이다. 이것은 집단 사고에 대한 Janis의 선형 모델의 한계를 제시하고 다른 관점의 필요성을 제시했다. 두 번째는 자기 조직적 관점에서 집단 사고 현상이 발생하는 시뮬레이션이었다. 시뮬레이션 실험의 결과는 집단 사고가 협력적인 상황에서 자연스럽게 일어날 수 있는 현상이라는 것을 보여주었다. 이 연구의 결과는 집단적 사고 현상을 조직으로부터 완전히 제거하는 것보다 적절한 조치를 통해 생산적으로 만드는 것이 더 중요하다는 것을 보여준다.

두 번째 연구인 "The optimal knowledge creation strategy of organizations in groupthink situations"의 목표는 두 가지다. 첫째, 집단사고에서 조직의 전환 요인을 파악하여 집단지능으로 전환하고, 둘째, 전환 요인을 활용한 최적 전략을 조사한다. 본 연구에서는 지식 충돌, 대안의 재고, 조직 기억의 세 가지 요소가 선행 문헌들에서 도출되었다. 세 가지 전환 요인의 효과를 검증하기 위해 행위자 기반 모델 시뮬레이션을 실시하였고, 그 결과 모든 전환 요인이 조직 지식의 질을 향상시키는 데 효과적으로 나타났으나 다양성 증대에는 큰 효과가 없었다. 전환 요인에 기초한 최적의 전략을 도출하기 위해, 시뮬레이션의 메타 데이터를 활용하여 메타 프런티어 분석을 수행했다. 그 결과는 지식 충돌과 대안의 재고의 조합이 가장 효율성이 높은 반면 지식 충돌과 조직 기억의 조합은 효율성이

가장 낮다는 것을 보여준다.

마지막 연구인 "Effect of emerging technologies on the organizational knowledge creation: the use of big data analytics and online platforms"는 연구에서는 신기술의 활용이 조직 지식의 생산에 어떤 영향을 미치는지 파악했다. 이 연구는 빅데이터의 사용과 온라인 플랫폼 사용에 초점을 맞췄다. 조사 데이터를 바탕으로 각 기술이 집단 사고와 집단 지능에 미치는 영향을 파악하였다. 이 연구의 결과는

본 논문은 상기 연구를 통해 조직 지식창출 과정의 효율성을 높이고 조직 전략과 기술적 측면의 양질의 지식을 창출하는 방법을 제시했다. 전환 요인을 활용한 조직 전략 수립 가이드라인을 제시하고, 빅데이터 분석 기술의 활용과 온라인 플랫폼의 활용을 통해 사회기술적(socio-technology) 관점에서의 전략을 제시한다.

주요어 : 지식경영, 조직동학, 집단지성, 집단사고, 행위자기반모형, 사회적기술
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