M.S. Thesis in Engineering

The Effect of Incentive Mechanism on Knowledge Transfer Network

: An Agent-Based Model Approach

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이 논문을 공학석사학위 논문으로 제출함

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Abstract

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Knowledge transfer plays a vital role in the growth and sustainability of organizations. Organizations can prevent knowledge loss and promote innovation through this activity. Moreover, access to knowledge can reduce mistakes because it records past errors that others have already made so that the recurrence of the same mistakes will not happen in the future. Knowledge transfer also creates opportunities for employees to work together and share ideas which are helpful for their professional development. Organizations can keep innovating, improving, and competing in a rapidly changing environment if they maintain knowledge properly. Unfortunately, rational individuals tend only to participate in knowledge transfer if the benefits generated exceed the costs.

Incentives motivate people to perform. There are many types of incentives, but we will focus on material incentives for this research. Material incentives vary from salaries to compensation packages or stock option programs in a firm setting. As individuals tend to monopolize knowledge, incentive mechanisms could be one factor that eases that desire.

This research aims to analyze the effect of incentive mechanisms on knowledge transfer activities.

This research uses an agent-based model approach to simulate knowledge transfer activities within an organization. An agent has a set of attributes and behaviors that resembles an employee. We assume that knowledge transfer happens when agents interact with each other. Based on the interaction history of each agent, we will construct a knowledge transfer network. We expect an agent to form more connections in the existence of an incentive mechanism.

The result suggests that incentive mechanisms positively correlated with knowledge transfer efficiency. However, the effect is not significant to change the network structure. This implication offers valuable insight into organizational practices. Managers should focus on the quality of people instead of quantity and investigate other factors that can motivate them to participate in knowledge transfer activities.

Keywords: knowledge transfer, incentive mechanisms, agent-based model, network structure

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Chapter 1. Introduction

1.1 Research motivation and background

Rapid technological change has become a challenge for companies to stay ahead of the competition. They should adapt well to the changing business environment by understanding consumer needs better and seizing market opportunities. However, companies often neglect this aspect by prioritizing short-term goals. Previous studies suggested that effective and efficient knowledge transfer processes will support sustainable competitive advantage (Chen, 2010). The knowledge transfer will help companies to align their strength and create innovation. Companies that successfully implement knowledge transfer respond more effectively to new market opportunities and changes. Moreover, they can also create new ideas and business opportunities (Hussein et al., 2016).

The key to successful knowledge transfer activities is understanding people's needs and motivations. Knowledge has values that can be collected, calculated, or lost. As rational individuals, it is normal for people to use their knowledge for maximum profit. They will only share their knowledge if the benefits generated exceed the cost. Several reasons make individuals act positively in knowledge transfer, mainly related to acknowledgment and conscience. They want to be viewed as experts and desire credit and recognition. Those who are willing to share their knowledge feel a moral obligation to do so because they view knowledge as a public good (Wasko & Farja, 2000). In contrast, people are unwilling to share their proprietary knowledge because they perceive it as a competitive advantage. They fear that they will lose power and control by sharing with others. Another reason is the fear of making mistakes. They are afraid to be ridiculed or criticized if the knowledge they share is wrong (Gilmour, 2003).

Previous studies examined the roles of some factors, such as organizational climate, social-psychological forces, and extrinsic motivators, to better understand people's intention in sharing knowledge. The intention to share knowledge will be more significant as the attitude toward knowledge sharing becomes positive (Bock et al., 2005). A sense of self-worth, anticipated rewards, and reciprocal relationships primarily drive this attitude. Managers can use these factors to encourage employees to share their valuable knowledge. Good company culture will nurture a sense of self-worth and reciprocal relationships, while the incentive design will give employees the payoff for their efforts. Therefore, many companies use the reward mechanism to encourage internal knowledge transfer.

Organizational rewards are beneficial because they motivate individuals to perform expected behaviors (Bartol & Locke, 2000). The rewards could be intrinsic, such as the pleasure of performing the task, or extrinsic, such as monetary rewards, gift certificates, and public recognition. Wolfe and Loraas (2008) discovered that rewards can promote knowledge transfer, whether monetary or non-monetary. Meanwhile, Bartol and Srivastava (2002) suggested that rewards will only be effective for a specific type of knowledge-sharing activity. Monetary rewards, such as bonuses, are appropriate to encourage knowledge sharing through individual contribution and formal interactions within or across work units. As for knowledge sharing through informal interactions, intangible rewards such as recognition is more suitable.

One aspect of organizational reward systems that helps motivate individuals to perform the targeted behaviors is the perceived fairness of rewards. However, the invisible nature of knowledge makes it challenging to observe knowledge transfer processes. We cannot measure the precise amount of effort everyone gives during the process. Previous research measured the effect of incentive schemes by calculating the difference in performance or output. They gather the data through interviews, surveys, and questionnaires because the information is not publicly open. A drawback of this method is that we can only evaluate the currently implemented or past incentive schemes. Moreover, we cannot inspect the process because we only get the final result. We use the simulation method in this research to overcome those drawbacks. Even though we are not dealing with prediction in this research, we can see how incentive mechanisms will transform the knowledge transfer process within an organization.

Each individual has different preferences. We need to examine the interaction results between these complex individuals to understand the knowledge transfer process in the organization. Given the circumstances, this research uses agent-based simulation to model the interactions in an artificial environment where the agent is either willing to share or does not share knowledge. The incentive mechanism will be integrated into this model to show the changes in interaction patterns. Prior research widely used the agent-based modeling and simulation (ABMS) approach to study knowledge transfer. The ABMS approach enables researchers to control individual behavior as variables of an agent and think through how the behavior of a single agent influences collective behaviors.

1.2 Research purpose and outline of the study

This study aims to analyze the effect of incentive mechanisms on the knowledge transfer network. This study uses agent-based model simulation (ABMS) and social network analysis as the knowledge transfer process occurs in a complex system. The focus of this study is knowledge transfer activity in the industrial setting. First, this study defines a set of attributes and behaviors to reflect the characteristics of employees in a traditional company. Then, some renowned incentive strategies will be embedded in the virtual environment where the agents interact to replicate the incentive mechanism. Finally, this study analyzes the interaction history between agents to determine the form of the network in the absence and the presence of various incentive strategies.

This research consists of five chapters. Chapter 2 reviews the previous literature on knowledge management, especially knowledge transfer activity and ABMS for knowledge sharing. As previous research has rarely considered incentive mechanisms for analyzing the knowledge transfer process, this study introduces the ecosystem of company rewards and then addresses the perceptions of each employee. Furthermore, this study defines research questions regarding knowledge sharing by systematically analyzing the prior use of simulation models for knowledge sharing.

Chapter 3 focuses on the development of the model and simulation settings. This chapter identifies the required attributes and behaviors representing knowledge transfer activity and explains how the simulation works. Chapter 4 presents the simulation results and analysis. Based on different settings in each simulation, a data set is obtained and further analyzed. Finally, Chapter 5 concludes this study. It outlines implications for research into knowledge transfer and industrial policy. Based on the analysis results presented in the previous chapters, this chapter discusses limitations and future directions.

1.3 Research Questions and Hypothesis

Previous theoretical research on knowledge transfer and incentives mechanism has presented questions that develop current issues and help to overcome the limitation of previous studies. First, an analysis of the knowledge transfer process on the presence of incentives is needed. Some prior studies have discussed the relationship between knowledge transfer activity and intrinsic or extrinsic incentives. However, most of the studies focus on the knowledge transfer result, for example, by examining the firm's overall performance. As they focus on performance metrics, the perception of individuals and interactions among them are hardly considered.

Table 1 summarizes previous studies that discuss the effect of incentives on knowledge transfer activity. Chang and Coyte (2014) conducted a scenario-based experiment to measure knowledge transfer activity in the presence of incentives. This approach is unusual because most studies evaluate existing policies or incentive mechanisms currently applied. Wickramasinghe and Widyaratne (2012) asked the employees regarding their perception of rewards to know the correlation between incentives and knowledge transfer. Another study utilized employee self-report to analyze the effects that may occur from the implementation of incentive mechanisms (Lombardi et al., 2020). Other studies use questionnaires and surveys with different constructs to reveal the correlations (Hu & Randel, 2014; Zhang et al., 2013; Ho & Kuo, 2013). In addition, only a few include social interaction as a factor affecting knowledge transfer effectiveness.

Because most of the previous studies focus on the result of applied incentive mechanisms, we need to wait a certain period to determine whether our incentive mechanisms have a positive or negative effect. This research aims to design a new approach to enable early prediction of the incentive mechanisms' outcomes. By defining the employees' behavior as an agent model and simulating knowledge transfer between them, we can foresee the expected result of incentive mechanism application.

Second, an analysis of the structure of the knowledge transfer network should be developed. Previous literature suggests that the network form influences knowledge transfer performance. They restrict their research by predefining the network type instead of watching how it naturally formed. It prevents us from observing what makes people build connections regarding the knowledge transfer purpose. We can analyze how the knowledge transfer network is formed by observing the pattern created by the interaction between agents using the agent-based model simulation.

Based on the need for further research, as explained above, the following research questions arise:

1. What type can knowledge transfer networks be categorized into by default?
2. What is the effect of incentive mechanisms on knowledge transfer in terms of efficiency and the network structure?

Table 1. Comparation of Previous Studies

Study	Social Interaction Related	Incentive Type	Incentive Measurement	Incentive and Knowledge Transfer Correlation
Wickramasinghe & Widyaratne, 2012	No	Extrinsic and intrinsic	Perception towards rewards	Positive
Lombardi et,al, 2020	Yes	Extrinsic	Employee self-report	Negative
Cheng & Coyte, 2014	No	Extrinsic	Scenario-based experiment	Positive
Hu & Randel, 2014	Yes	Extrinsic	Team leaders and members questionnaire	Positive
Zhang et.al., 2013	Yes	Extrinsic	Cross-sectional survey	Positive (with visibility), otherwise insignificant
Ho & Kuo, 2013	No	Extrinsic and intrinsic	Questionnaire	No effect (material), positive (social)

According to network theory, new nodes in most real networks prefer to link with the more connected node. This behaviour is publicly known as a preferential attachment. Consider this example for more context. No researchers can read millions of scientific papers published each year. However, the more cited a paper, the more likely we find it and cite it in our publication. By adding that citation, we already made our publication biased toward the high-degree nodes of the citation network. This phenomenon can also apply to knowledge transfer networks. Any nodes will prefer to make a relationship with "knowledge-rich" nodes. It will cause a few highly connected nodes (hub) to coexist with many small nodes. Therefore, this study has the following hypothesis:

1. The knowledge transfer network is scale-free because of the preferential attachment to high knowledge nodes.
2. The existence of an incentive mechanism will change the network structure into a random regime as the possibility of making connections with any nodes becomes higher.

Chapter 2. Literature Review

2.1 Definition of Knowledge Transfer

2.1.1 Theoretical Perspectives of Knowledge Transfer

According to Carlile and Rebentisch (2003), knowledge transfer is a branch of knowledge management that deals with the movement of knowledge across barriers formed by specialized knowledge domains. It is challenging to comprehend and put into practice because there needs to be a precise definition or proven method for effectively transferring knowledge. Adapted from Christensen (2003), knowledge transfer is the process of locating (available) knowledge that already exists, learning it, and then using it to create new ideas or improve the existing ones in order to speed up, improve, or make a process or action safer than it otherwise would have been. Knowledge transfer is about utilizing readily available resources, i.e., knowledge, and how to acquire and absorb it to improve processes effectively.

Knowledge sharing is essential in knowledge transfer (Nonaka & Takeuchi, 1991). Some believe that knowledge transfer and management are carried out primarily to foster a culture of knowledge sharing, improving organizational creativity through collaboration and communication (Liebowitz, 2002). Although knowledge transfer in organizations goes beyond this, knowledge sharing in organizations often involves the exchange of knowledge at the individual level. Argote and Ingram (2000) state that this includes knowledge transfer at higher levels such as group, product line, department, or division.

Conveying explicit or implicit knowledge requires effort on both the source's and recipient's sides. Individuals may communicate explicit or implicit knowledge. It is common practice to use verbal communication to share explicit knowledge. In his definition of the sharing of tacit knowledge, Nonaka (1994) proposed that the recipient could acquire tacit information from the source through socialization, observation, and apprenticeship. Giving the recipient more opportunities to work alongside would be the best method to benefit from a source of tacit knowledge. Nonaka also asserted that externalization, a process through which the knowledge source engages in elaborate communication using analogies, metaphors, and stories, could convey tacit information.

Knowledge transfer can be defined as the act of communication and translation (Liyanage et al., 2009). The ideas of translation and communication appear to be two distinct yet complementary theories for transferring knowledge. The former clarifies the behavioral aspect of knowledge transfer or the cooperative act between the source and the receiver; the latter, on the other hand, offers some guidance on how to transform knowledge into a useful form effectively. Suppose the parties involved are unwilling to share knowledge because of concerns about confidentiality, cultural barriers, or the fear of losing a competitive edge. In that case, a knowledge transfer process may frequently fail. Furthermore, it is asserted that knowledge transfer can only be effective if an organization cannot only receive knowledge but also absorb it, digest it, and then effectively apply concepts, knowledge tools, and artifacts.

The translation theory incorporates three components to the process in the knowledge transfer model. The network (or networking) is the first component. Close and tight contacts between individuals, teams, and organizations are essential for information transfer methods to be effective in organizations. Networks enable this close cooperation between and among entities, i.e., individuals, individuals and teams, teams, and teams and organizations. Organizations can develop and coordinate acquired knowledge more effectively thanks to close interactions.

Second, the translation theory emphasizes the necessity of identifying any limitations placed on the transfer process. Identification of these potential factors and their amount of influence on the process is crucial to determining the success or failure of a knowledge transfer process. People and organizations share a variety of context-related factors, such as culture, capacities, skills, management styles, politics, technology, etc. Each of these factors can have a good or negative impact on the knowledge transfer process. These influencing factors are roughly divided into two categories in the established model: inner influences and external effects.

The translation theory also emphasizes the need to evaluate the final product's degree of accuracy and quality. Organizations will only be able to determine the accomplishments and efficacy of the knowledge transfer process if they try to evaluate the reliability and caliber of the knowledge obtained. The lack of evaluation will lead to neglecting to acknowledge the impact it had on the organizations and its practices and repeating the same errors in future knowledge transfer procedures. Therefore, performance measurements should be conducted as part of the knowledge transfer process (Liyanage et al., 2009).

2.1.2 Agent-based Model for Knowledge Transfer

The knowledge transfer activity within an organization is complex since it involves local phenomena (interactions between agents) with effects on the organization. In this way, the dynamics of knowledge spread are greatly influenced by everything that defines the interactions, what agents know about one another, and whom they can communicate. Because of its complexity, it is difficult to predict the effects of a local model at the global scale, which is why modeling tools must be carefully chosen (Kirman, 2004). Regularities observed at the individual and global level do not always simply and directly correspond.

An agent-based model is a tool that has lately been recognized as being suited to the knowledge transfer complexity, particularly in management and economics (Gilbert et al., 2001); this tool has also been frequently used in diffusion processes. Understanding how an aggregate phenomenon links to the underlying local mechanisms requires studying an organized complexity. The comparison of several situations is the strategy employed; for instance, it is rather usual to use various interaction mechanisms and evaluate their effects to determine their influence on global dynamics (Rouchier et al., 2001). One can better comprehend each new phenomenon's mechanism by creating several dynamics (Epstein, 2006).

A software agent is a computer program embedded in a specific environment and can behave autonomously there to achieve its intended goals (Wooldridge, 2002). Agents have four distinct qualities (Wooldridge & Jennings, 1995): *interactivity*, the capacity to interact, communicate, and collaborate with other agents; *reactivity*, the capacity to monitor and respond to changes in the environment in which they reside; *proactiveness*, the capacity to act on opportunities as they arise; and *autonomy*, the capacity to operate without direct human intervention.

When modeling business problems, agent-based simulation has several benefits over traditional simulation architectures. An agent is self-contained, proactive, adaptable, socially interactive, and cooperatively intelligent (Jung & Jo, 2000). An agent-based simulation system can therefore provide complex patterns of interaction (Jennings et al., 1998). Moreover, the agent-based model can examine the system's path within any timeframe. The behavior of the individual agents and the overall system can be tracked over time when an agent-based model is run in a simulation. Some factors, including utility, risk aversion, knowledge, and learning, are controllable. These components can be reset to different values through additional computer simulation runs to track differences in results. It is possible to evaluate each agent's strategies and outcomes in depth (Holland & Miller, 1991). Parameter values can be changed to investigate how the system's route responds to exogenous shocks (Parker et al., 2003).

2.2 Incentives Mechanism

2.2.1 Type of Incentives

Many researchers have employed the dichotomous technique, which separates incentives into intrinsic and extrinsic categories (Kwok & Gao, 2004). According to Deci (1976), extrinsic incentives are extra resources used to motivate people, such as money, promotions, profits, and professional advancement. However, intrinsic incentives are valued for their own sake and appear to be self-sustaining, and they also fulfill urgent needs. The intention and attitudes of employees who share their knowledge were found to be significantly influenced by both extrinsic motivational factors like reciprocal benefits and intrinsic motivational factors like knowledge self-efficacy and enjoyment of helping others, according to Lin (2007). Incentives undoubtedly influence behavior. People, however, have varied needs, so what drives each person can differ. The first step is to understand people's motivational needs. Once understood, a win-win outcome can be achieved by developing an incentive strategy (Greenberg & Liebman, 1990).

Another group of researchers divided incentives into different categories. For instance, Bock et al. (2005) identified three factors that affect people's attitudes toward knowledge sharing. The first is expected reward, which refers to how one can receive extrinsic incentives based on one's knowledge sharing behaviors. The second is expected association, which refers to strengthening mutual relationships through knowledge sharing. The third factor is expected contributions, which refers to how one can contribute to the knowledge sharing activity.

Additionally, Greenberg and Liebman (1990) proposed three types of incentives: activity, social, and material. The complexity of stock option programs or compensation packages might be as simple as straight pay or sophisticated as other material incentives. Social rewards are powerful motivational reinforcers that act on an interpersonal level by letting people identify with the business, coworkers, clients, or rival businesses. Activity incentives offer the opportunity to meet individual demands for growth or achievement by presenting more novel and challenging tasks. The constructs of the Greenberg and Liebman model are better suited for a community environment, whereas Bock et al.'s theory is intended to be implemented in an organizational setting.

2.2.2 Incentives and Knowledge Transfer

Previous studies have shown that real or perceived incentives motivate workers to share knowledge. For instance, Choi et al. (2008) offer proof that reward mechanisms are more crucial than technical assistance in promoting knowledge sharing. According to Bartol and Srivastava (2002), financial incentives may promote knowledge sharing through individual database contributions, formal contacts inside and across teams, and information sharing between work units. According to Wolfe and Loraas' (2008) research, incentives for information sharing may only be perceived as adequate by people if they consider their subjective definitions of incentives to be fulfilled. Therefore, they support tracking people's perceptions of how much of an incentive they perceive to be providing.

Understanding whether such incentives will encourage people to share their knowledge is crucial. As a result of the cognitive evaluation theory's (Deci & Ryan, 1985) claim that extrinsic rewards, such as monetary awards, will have a detrimental effect on intrinsic motivation, this question becomes pertinent. Briefly stated, the theory is that a person's sense of self-determination and competence drives them to execute tasks out of intrinsic motivation, which is defined as being motivated to do something because doing it makes the person happy.

In the case of extrinsic rewards, the individual would regard the locus of causality of behavior on engaging in or completing a target behavior as an external condition, which undermines their sense of self-determination and lowers their intrinsic motivation. Extrinsic rewards can also provide a message that a person is competent, which positively affects intrinsic motivation. As a result of these opposing pressures, it is not easy to foresee how extrinsic rewards would affect the intrinsic drive. Deci et al. (1999) discovered that rewards conditioned on the accomplishment of behavior had no impact on a person's interest in the task but had an overall negative impact on free-choice behavior. On the other hand, Eisenberger et al. (1999) discovered that extrinsic rewards had a favorable effect on sentiments of self-determination that are helpful for intrinsic motivation in a meta-analysis of studies that examined self-determination.

Chapter 3. Methodology

3.1 Model Development

This research will simulate the knowledge transfer phenomenon in a firm or industrial setting. Therefore, each agent in this model represents an employee. Everyone has different levels of knowledge, and it also applies to the agent in our model. Knowledge level has dynamic value. It can accumulate or decrease over time. Knowledge transfer happens when agents share some of their knowledge with other agents. Each agent keeps the history of all agents involved in the knowledge transfer with himself. Based on this interaction history, we can analyze the type of network formed due to the knowledge transfer.

As we discussed before, some barriers hinder knowledge transfer between employees. Incentive systems are designed to overcome that problem. It is expected that incentives will motivate employees to share knowledge with their coworkers. Some types of incentives include monetary rewards, promotions, public recognition, and job security. In this research, we will only focus on incentives in terms of rewards or bonuses. Incentives can be given to an individual or a group of employees. Some previous studies have already discussed the better method between those two. It was argued that individual incentives are less effective compared to group-based ones. It may lead to individualistic behavior and hamper the positive effect of informal coordination between employees on knowledge sharing (Lombardi et al., 2020). Therefore, we will adopt several mechanisms of group-based incentives into this model.

3.1.1 Agent Description

The main attribute of our agent is knowledge level. A series of binary strings with variable lengths represents every agent's knowledge. The binary strings illustrate fragments of knowledge. It means there are several knowledge fragments to acquire: if the agent does not have it, the bit value is 0, and 1 otherwise. This knowledge representation is in line with the nature of cognition, which follows combinatory rules instead of additional rules (Morone & Taylor, 2003). Agents have different states of initial knowledge level as it will represent the structure of the organization. Those who have higher initial knowledge have higher positions in the organization. The knowledge level will increase when an agent collects new information from other agents.

knowledge fraction	1	2	3	...	49	50
doesn't have (0) / has (1)	0	0	1		1	0

Figure 1. Knowledge Vector

In the real world, individuals have different capabilities in searching for new information. This model defines the knowledge vision attribute as the representation of that characteristic. Knowledge vision shows a range relative to the individual where he can detect new information. The range is implemented using the von Neumann extended neighborhood distance of each agent. The higher the searching ability of an agent, the higher the knowledge vision it has. This value is assigned randomly at the beginning of the simulation. Based on this value, agents will move around the virtual space to update their neighborhood status.

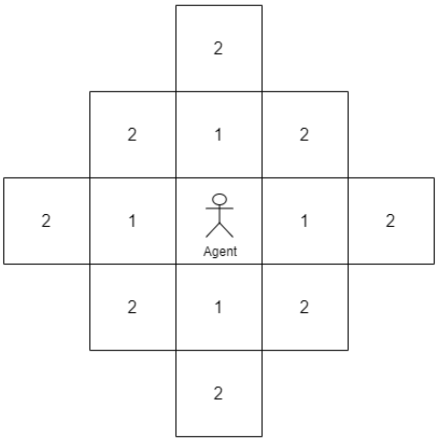

Figure 2. Von Neumann neighborhood diagram

Aside from being self-acquired, knowledge also comes from other coworkers. Employees usually work in a team, and knowledge transfer may happen during the interaction between team members. In this model, the agent will request knowledge from any agent within its knowledge vision. There may be more than one source from which an agent can request the knowledge. We can solve this problem by assuming that an agent knows the other agent's level of knowledge. As a rational individual, an agent will always choose the one that is most beneficial among the possible candidates. An agent can be a knowledge sharer or hoarder. It will be up to each agent to provide the knowledge. Their decision will be determined by the scenario we use during the simulation. Agents also have a tolerance level that defines the accepted number of unanswered requests. They will move to another point if they do not get a reply after sending requests that exceed their tolerance level. The following table summarizes the attributes that an agent has.

Table 2. Definition of agent's attribute

Name	Description
Knowledge level	Total knowledge fraction owns by an agent
Knowledge vision	The ability to detect knowledge from the surroundings
Tolerance	Maximum acceptable number of unanswered questions
Share tendency	Probability of an agent sharing their knowledge

Agent's behaviors mimic the daily habits of an employee in a work environment. We simplify those habits into simple actions in this simulation. In every tick, agents will try to collect new information if other agents are in their surroundings. The agent will choose any knowledge fragment they do not have and ask for that specific fragment from the nearby agents. If the agents do not have neighboring agents or their tolerance level is already exceeded, they will move to a new space. The last action represents personnel movements within the organization. This behavior is similar to when an employee moves around the organization dynamically; for example, employees might spend four months in the purchasing team before moving to the sales team. Personnel movement results from expansion, training programs, termination, or voluntary exit from other employees. It can be for short or long periods, but not permanent. Therefore, the agent's movement is determined by probability value. In each clock tick, an agent can change position randomly.

3.1.2 Incentive Design

Incentives will be given to employees for their efforts in transferring knowledge. In that case, this research uses performance reports as the baseline to determine the incentive value. This performance report will evaluate the agent's participation in knowledge transfer interaction. This research expresses knowledge transfer as an exchange of questions and answers among agents. Therefore, the agent's performance will be calculated from the ratio between the number of questions they get and the number of answers they give. This principle also applies at the organizational level. As we focus on group-based incentives, we need to sum up the total questions asked and how many of those are getting answered as shown in Eq 1 and 2.

$$performance = \frac{num\ of\ anwers}{num\ of\ questions} \quad \text{Eq 1}$$

$$E = \sum_i^N performance_i \quad \text{Eq 2}$$

E describes the firm's performance that accumulates the performance of individuals. The following assumption is that the agent perceives the value resulting from Eq 2 as the reward they will get from participating in knowledge transfer. Given the information on the firm's performance, we can define the expected return that each agent has:

$$return = \frac{E_{answers}}{N} \quad \text{Eq 3}$$

Eq 3 gives us the anticipated return that the agent expects. It shows the worth of the knowledge they share. As the calculation comes from collective effort, there is a risk of a free-riding problem. Risk calculation will be different depending on the incentive strategy we use. There are three strategies that we use in this simulation; they are partnership scheme, target-based scheme, and tournament-based scheme.

a. Partnership scheme

This scheme can be compared to standard revenue sharing, in which the firm's total revenue from performance improvement is equally distributed to all employees. In this type of scheme, the risk facing an agent is the participation level of other agents. Knowledge sharing is more likely to happen as the overall participation rate increases. They will only benefit if a considerable number of employees participate. Agents will consider to whom they will share the knowledge based on the receiver's performance. Therefore, the risk in a partnership scheme is equal to the individual performance status, as shown in Eq 4.

$$risk_{partnership} = performance \quad \cdots\cdots \text{Eq 4}$$

b. Target-based scheme

Forcing contract mechanisms is the general idea of this scheme. Outcome targets will be set for the entire firm or a group within the firm, and the employees are forced to meet the target if they want to receive the incentive. They will share all the revenue generated if the target is achieved and get nothing otherwise. In this study, the target will be the performance level in the organization's scope. The target achieved probability is the risk facing each agent in this incentive scheme type. A higher probability means a higher possibility of sharing knowledge with other agents.

$$risk_{team-based} = \Pr\left(\frac{E_{answers}}{E_{questions}} > target\right) \cdots\cdots \text{Eq 5}$$

As shown in Eq 5, agents will assess the recent overall performance as it reflects other agents' participation level as a group. Unlike the partnership scheme, accumulated individual performance is less relevant in this incentive scheme because a specific target should be achieved.

c. Tournament-based scheme

Contrary to target-based incentives, this scheme uses a relative performance threshold rather than a fixed one. This scheme is a competitive team mechanism as we divide the employees into two or more groups and have these groups compete for rewards. This mechanism relies on competition to motivate the employee. The group that performs better will get the reward, while the losing team will get nothing. The risk agents face in this tournament-based scheme is the winning probability of their team.

$$risk_{tourney-based} = \Pr\left(E_{G=1} > E_{G\neq 1}\right) \cdots\cdots \text{Eq 6}$$

Let G represent the team to which an employee belongs. For all employees that are part of Team 1, the risk they face is the probability that their team ($G=1$) performs better than other teams ($G \neq 1$). The target value is dynamic because it depends on the performance of other teams. This study will divide agents into two identical groups for the simplicity of the simulation.

3.2 Simulation

This study applies the ABMS approach to analyze the correlation between monetary rewards and knowledge transfer efficiency under different group-based incentive schemes. Mainly, the method consists of four phases: setup agents that represent employees of a firm or company who ask or share knowledge with their coworkers, model the environment where agents exchange information under behavioral rules, define ABMS for knowledge transfer procedure, and investigate the influence of external incentives on knowledge transfer.

3.2.1 Environment Setting

This study aims to explore the influence of incentives on knowledge transfer efficiency. Therefore, we consider knowledge completeness as the dependent variable in this study. The value ranges from 0 to 1, representing the knowledge fragment portion an agent possesses. Agents will reach the complete knowledge state if they successfully collect all the knowledge fragments. The virtual space where the agents interact with each other reflects a company space. We can set the size of this space by modifying the number of squares (*L*), which will define a square space with *L* x *L* dimension. This simulation uses a constant size of space (*L=20*) equivalent to an average organization's size (Kowalskastyczeå et al., 2018).

The initial value of knowledge level is also set using a fixed proportion to reflect the hierarchy within the organization. Among the agents, one agent will have complete knowledge, 10% of them will have half of the maximum number of knowledge fragment, and the rest of them do not have any knowledge fragments (zero-level knowledge). Besides the maximum number of knowledge fragments (*M*), this simulation also defines several independent variables as follows:

a. Number of employees (*N*)

   This variable defines the number of agents needed for the simulation. As this simulation uses a fixed-size space, a higher value of *N* means a higher density. In every experiment, we set the number of employees to 150 because it is the maximum number of relationships a person may accept. This number follows a prior study's finding that people may easily maintain only 150 stable relationships (Purves et al., 2013).

b. Tolerance level (*T*)

The agents will keep asking to a same partner as many as their tolerance level to acquire knowledge. They will ask another agent if the tolerance limit is exceeded. All agents in this simulation have an equal tolerance value. To determine the tolerance level in this study, we run several simulations under different conditions to understand the effect of tolerance on knowledge transfer efficiency. The result reveals that knowledge transfer efficiency gradually improves when we add the tolerance level. However, the efficiency becomes inconsistent when we use a tolerance level of six and above. Therefore, we set the tolerance level to 5 for all experiments in this study.

c. Vision range (*V*)

This variable determines the range of the agent's movement. A high vision range means a high knowledge awareness. The agents will move in a broader range because they know more agents who possess the necessary knowledge. Each agent has a different vision range randomly assigned in the initialization stage. The value will vary from 1 to maximum value. According to Hirshman et al. (2011), a core discussion group should have three to five members, usually fewer than six. An agent can find five other agents within its three von Neumann neighborhood distances based on the current setting. Therefore, the maximum value is set to three for all experiments.

d. Knowledge Fragment (*M*)

Knowledge fragments can be translated as the total amount of knowledge within the organization. Based on the study by Li et al. (2021), we set the number of knowledge fragments to 20 for the consideration of effectual numerical simulation. It means that the agent should collect all twenty pieces to reach the state of complete knowledge.

e. Performance target (*R*)

This variable sets the threshold value to determine the expected performance level of the agents. It only applies to target-based scheme scenarios. Based on the sensitivity test, the performance target does not significantly affect knowledge transfer efficiency. However, the level of participation reveals a different insight. Agents will participate more as we add the performance target ratio to 0.5. The participation level will decrease and remain constant beyond that ratio. Therefore, we set the performance target to 0.5 for all experiments to reflect the highest participation level of knowledge transfer.

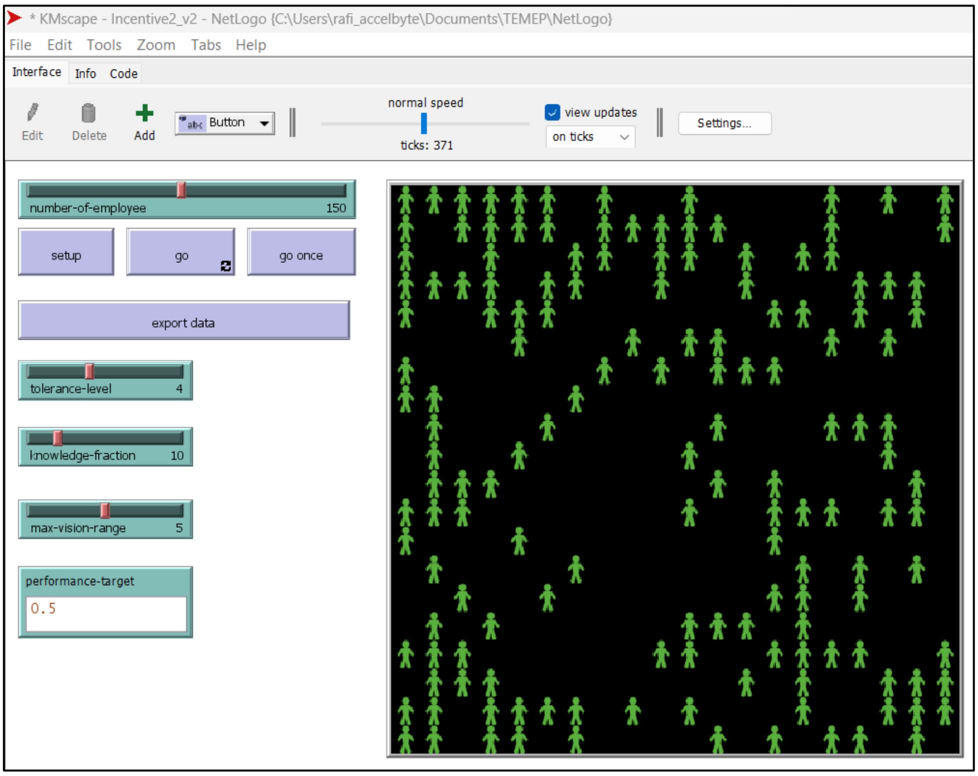

Figure 3. Variables for environment setting.

3.2.2 Interactive Rules

Previous studies have investigated the knowledge sharing utility as a measure of personal belief or intrinsic motivation (Pee, 2018). In economics, the utility concept allows individuals to choose an action that maximizes their goals among the possible options. This study proposes a decision model for individuals with knowledge. The model decides whether the agent should share the knowledge, given the likelihood of maximizing their utility function in terms of costs, return, and risk, as shown in Eq 7.

$$U_{share} = \text{cost} + \text{return} + \text{risk} \quad \cdots\cdots \text{Eq 7}$$

$$mono = 1 - \frac{n\,fragment_i}{N} \quad \cdots\cdots \text{Eq 8}$$

The cost of knowledge transfer is the monopoly of knowledge. The agents within the organization have a strong sense of monopoly on some rare types of knowledge. Therefore, the monopoly perception of agents towards a particular type of knowledge is modeled by the ratio between the number of agents who possess a specific type of knowledge and the total number of agents as shown in Eq 8. A high sense of monopoly indicates a stronger feeling, where the agent will be less likely to transfer the knowledge. The previous section already discussed the other two variables of utility functions. The return of knowledge transfer is the anticipated reward the agents will get after giving their knowledge. Meanwhile, the risk of knowledge transfer is the possibility that they will get less reward because of others' actions. The risk will differ depending on the incentive scheme strategies.

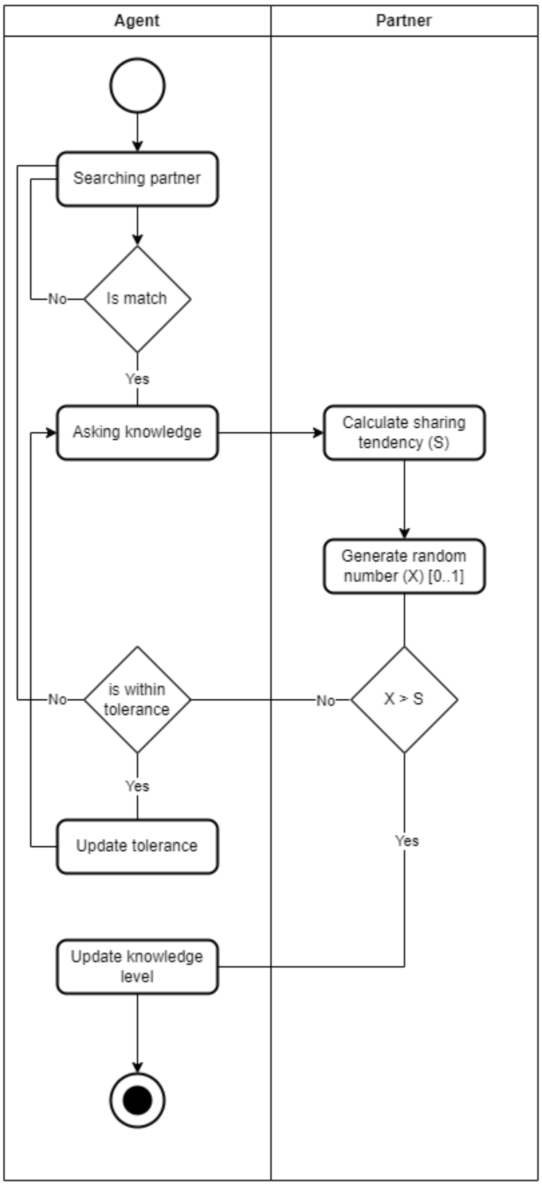

Figure 4. Decision model interaction diagram

In each round, the agents will perform the following behaviors in sequence:

1. Agents will check their surroundings to find a partner. If they see other agents nearby, they will randomly choose one agent that fits the criteria. The criteria for a partner is to have a knowledge fragment currently not possessed by the agent. If the agent cannot find a match, it will keep searching.
2. The agent will ask for knowledge from their partner. Utilizing the decision model, the partner will calculate their willingness to share. The system will generate and compare a random number to the calculation result. The partner will share knowledge if the random number is bigger than the sharing tendency. Otherwise, the partner will ignore the knowledge request.
3. When the agents do not get a reply from the partner, they will check their tolerance level. They will update their tolerance status and ask the same partner again if the rejection is within their tolerance level. Otherwise, they will search for a new partner.
4. If the partner shares knowledge, agents will update their knowledge status with the knowledge fragment given by the current partner.

3.3 Model Validation and Verification

The correctness of a model is essential to prove that the model helps answer real-world problems. It should provide accurate outputs that address the relevant issues. This study determines model accuracy through the validation and verification modelling process. Model validation refers to evaluating whether the proposed model explains and corresponds to some events in a real-world scenario. Meanwhile, model verification evaluates whether the proposed model represents the desired conceptual model. This step is similar to ensuring that the model is correctly implemented. Confidence in the correctness and explanatory capabilities of the proposed model will grow when we ensure that it conforms with the conceptual model and produces outputs that correspond to real-word phenomena.

3.3.1 Validation

This study used the method proposed by Rand and Rust (2011) to validate the proposed agent-based model. Many recent ABMS studies use this validation approach to confirm the validity of models by performing these three actions, namely micro-face validation, macro-face validation, and model input validation. Face validation is a method in which we should prove that the mechanisms and properties of the model resemble their counterpart in the real world by only looking at the model. A model cannot include all the patterns and characteristics of the real world because a model is a simple form of reality. We design a model according to the specific questions of a real-world phenomenon. Therefore, it is crucial to keep the questions in mind and validate parts of the models relevant to those questions during this process.

Micro validation refers to a process in which we should ensure the mechanisms and behaviours embedded into the agents fit their real-world representation. The model's attributes, assumptions, and decision-making process should be derived from formalized models of recent knowledge management and incentive-related studies. Agents' interaction during the knowledge transfer follows the knowledge barter theory (Cowan & Jonard, 2004). When two agents meet, the decision to ask for knowledge is based on what the other agent has to offer rather than how much the agent can give. Agents ask for knowledge to increase their competence. Knowledge is obtained from the answers of other agents. Each agent shares an equal tolerance level, the threshold of unanswered questions that could be accepted before they decide to ask other agents (Guechtouli et al., 2013). Agents who receive questions will choose an action that maximizes utility (Li et al., 2021). Lastly, agents will interact with other agents within their von Neumann neighbourhood (Jolly & Wakeland, 2009).

Macro validation confirms that aggregating agents' attributes and behaviour correspond to actual world events. The proposed model is consistent with the state of the art of ABMS and the empirical research on knowledge transfer (Kowalskastyczeå et al., 2018). Initial values are assigned to the model before the simulation start. Then, knowledge transfer between agents occurs under a particular condition (incentive-related perception) during the interaction phase.

Lastly, the number of agents with complete knowledge implies knowledge transfer efficiency (Roucher et al., 2013).

The parameters (M, N, T, and V) employed in the simulation studies are assessed regarding their impact on knowledge transfer between agents in terms of empirical input validation. The goal of this agent-based simulation model, which models choice behavior and incentive mechanism, is to provide insight into how well knowledge is transferred concerning perceived incentives. The results of this simulation experiment follow the same patterns as a prior study on the trust effect conducted by Li et al. in 2021. For instance, both the simulation results of this study and the trust study show that a higher tolerance level boosts the efficiency of partners' interaction.

3.3.2 Verification

Model verification is an approach to ensuring that the agents are carrying out their intended purpose. It means we should keep track of our code inside the implemented model. This study runs model verification through three basic steps, as stated in the standard practices for ABMS verification (Rand & Rust, 2011). The first step is to build the model based on formalized models, as we already discussed in the model validation process. The second step is performing step-by-step debugging for software integration and procedure testing. The last step is to design a set of test cases.

A procedure is the smallest unit of functionality inside the agents. Each procedure needs to be tested thoroughly to ensure the output meets our expectations. The written codes are carefully tracked and compared with the model specification to ensure that code implementation follows the expected flow and behavior. For example, to test the process of selecting a partner, the codes of the *select-partner* procedure are carefully debugged and inspected. Some test cases regarding this specific functionality, for instance, no agents around, there are agents but no matching knowledge, and there are agents with matching knowledge. Various possible test cases are executed to ensure the partner selection function has the desired output.

After carefully testing all procedures, we execute integration testing to examine the flow of the model. The test will use a set of different scenarios and parameter settings to check whether the procedures work well with each other. The test begins with a model with a small size (e.g., *number-of-employee* = 10) as the baseline. Due to the model's small size, the agent details in each step of the flow can be observed easily. Tests using more complicated models will be performed afterward.

Chapter 4. Result and Analysis

4.1 Knowledge Transfer Efficiency

The one-factor-at-a-time (OFAT) sensitivity analysis was used in this study because it was not necessary to identify the association between all parameters and the result. One parameter changes at a time while the other is held constant in an OFAT sensitivity analysis (ten Broeke et al., 2016). It helps examine the connection between a parameter's variation and the outcome. People density, tolerance threshold, knowledge vision range, and knowledge complexity were considered for testing the model's sensitivity.

The agents' objective in this simulation is to have complete knowledge by collecting all available knowledge fractions. The number of agents already completing their knowledge collection is the parameter of knowledge transfer efficiency. The faster the time needed for all agent to complete their collection, the more efficient the knowledge transfer process. We hypothesize that knowledge transfer efficiency will vary under different incentive schemes. The following sections will compare each incentive strategy's effect on knowledge transfer efficiency under different variable settings.

4.1.1 Density

The *number-of-employee* variable value determines the agents' density as we keep the virtual space size constant. Overall, knowledge transfer efficiency positively correlated with the density of agents. The efficiency increases as the density goes up. This behaviour is particularly evident under the partnership scheme. However, there is an optimum density value in the case of target-based and competition-

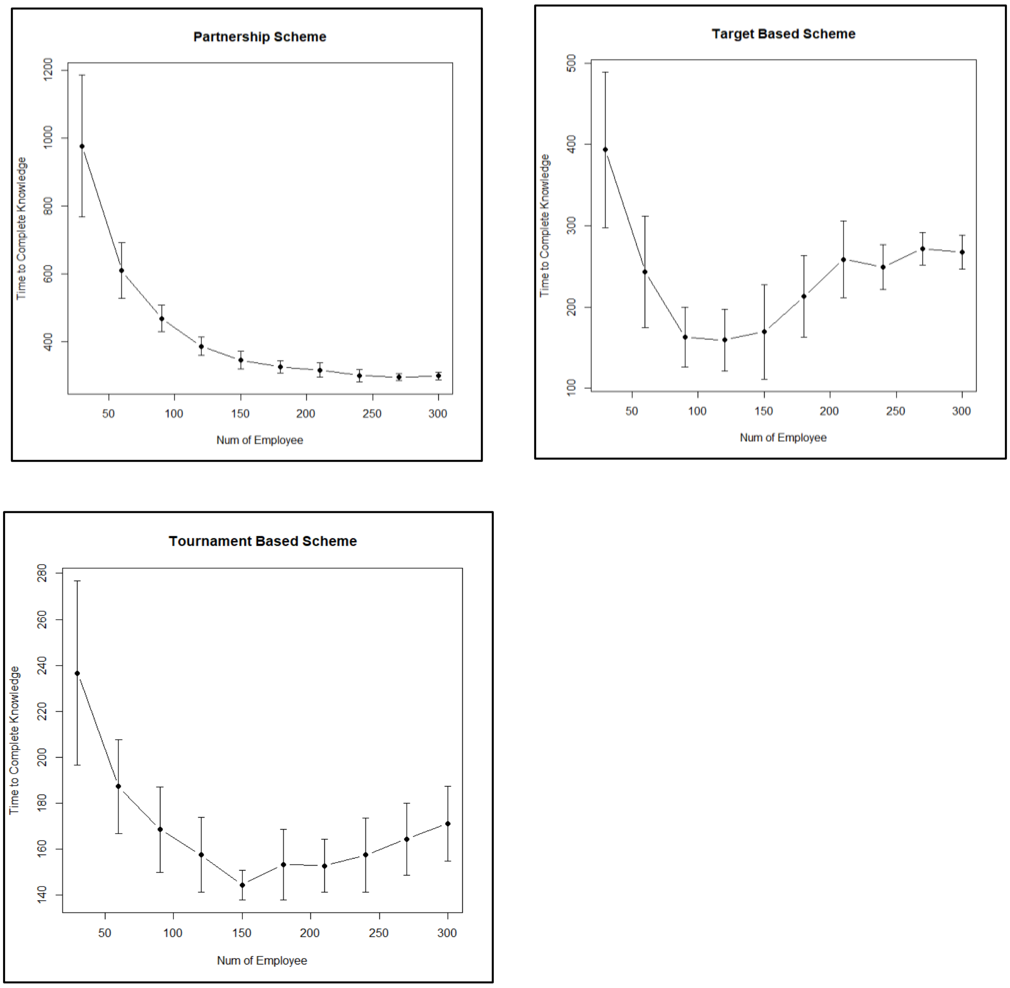

Figure 5. Knowledge efficiency by company size

based schemes. In both cases, the time needed to reach knowledge completeness gradually decreases until a certain point. We can see from Figure 5 that the curve starts to go upward when it exceeds 150 agents.

4.1.2 Tolerance

Each agent has the same tolerance level. In a way, *tolerance-level* values describe how dynamic the simulation is. There will be more movement when the tolerance level is low because agents will immediately look for another agent when they do not get the needed knowledge. All three schemes have a similar influence on the efficiency of knowledge transfer. The time needed to collect all knowledge has a decreasing trend even though the value is slightly fluctuating. However, the efficiency under the target-based scheme has a significant increase after it passes the mean tolerance level, as shown in Figure 6.

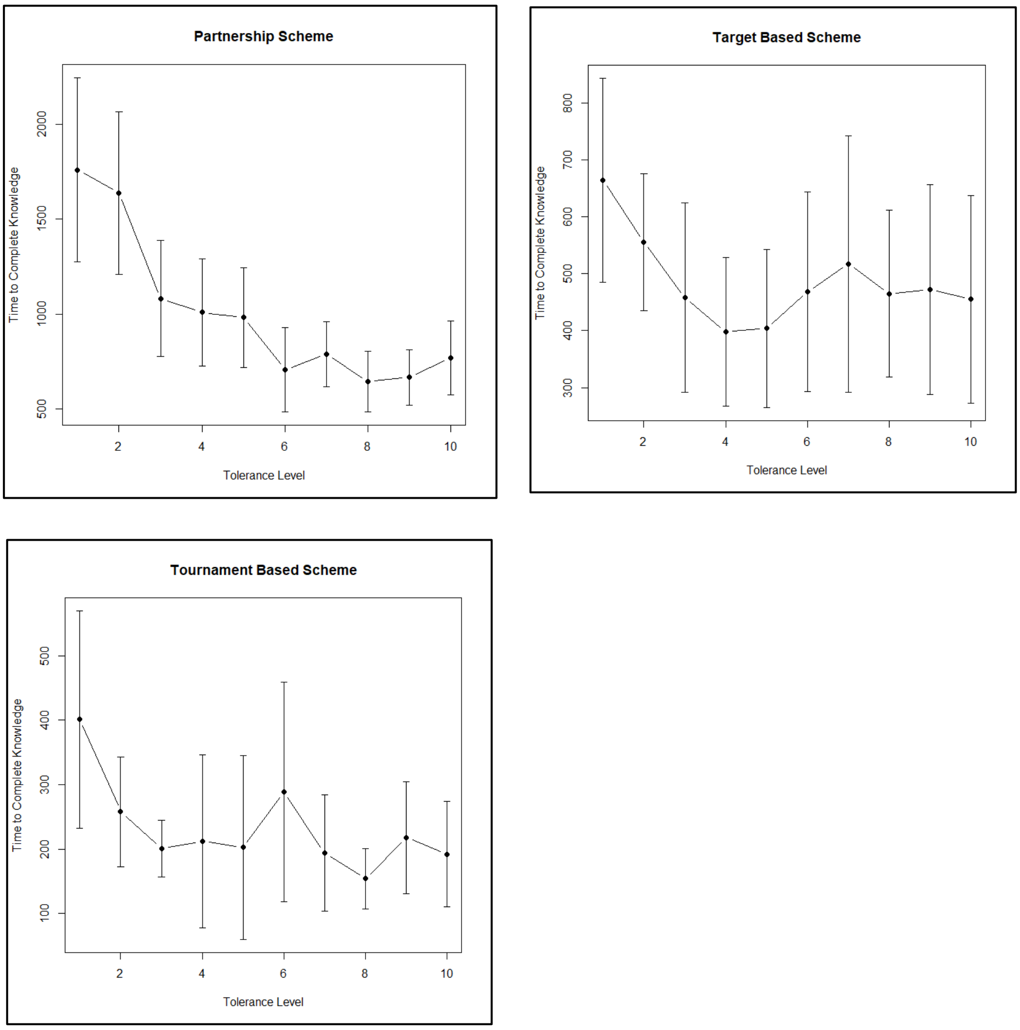

Figure 6. Knowledge efficiency based on tolerance level.

4.1.3 Knowledge Vision

Knowledge awareness is the agent's ability to pinpoint the location of "required" knowledge. A high level of awareness means the agent can identify the most suitable source of knowledge. In this simulation, knowledge vision represents awareness of the agents because it determines the area in which they can search for needed knowledge fraction. The more comprehensive the search range, the more agents they can contact, and the more significant probability of finding the most suitable one. The simulation results reflect that principle well. From Figure 7, we can see that knowledge efficiency increases when the agents have a high vision range value. The time to complete knowledge collection decreases significantly up to the mean value of the vision range, and then the slope becomes

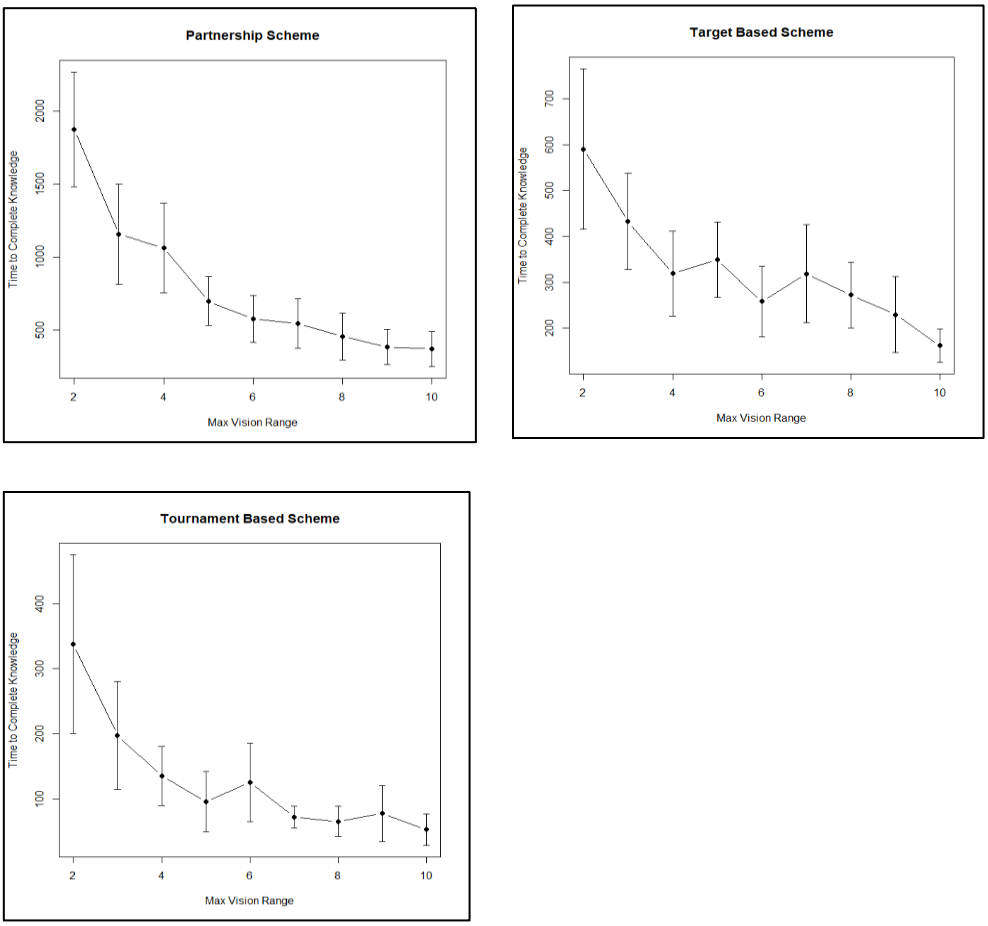

Figure 7. Knowledge efficiency based on vision range.

less steep.

4.1.4 Knowledge Fraction

From the knowledge diffusion model perspective, knowledge will be best represented as a vector. We called a single value in the vector a “knowledge fraction”. The large number of fractions indicates a more significant effort to reach complete knowledge, as many fractions exist to collect. Naturally, we expect it will take longer to complete the knowledge because the agents need more interactions than usual. The knowledge transfer process efficiency is decreasing in all three schemes. As more fractions are required to complete the knowledge, the time increases gradually.

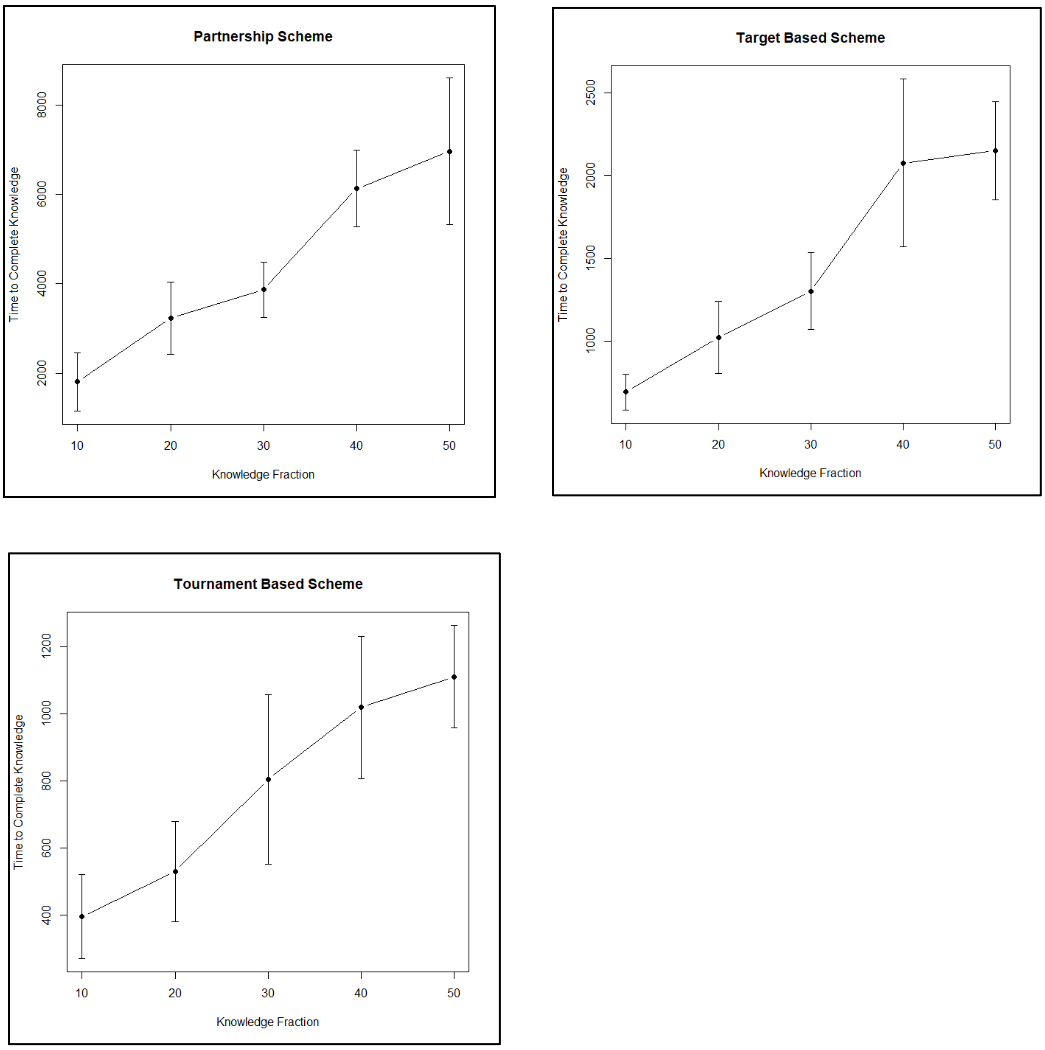

Figure 8. Knowledge efficiency based on complexity.

4.1.5 Performance Target

This variable only applies to target-based schemes. The agents in this study consider performance targets as a risk in their utility function. If the performance target is too high, the agents will perceive that they will not get any rewards no matter how much knowledge they share. Surprisingly, the performance target does not significantly decrease the efficiency of knowledge transfer. In some cases, a greater performance target yields better efficiency. The result is consistent with the agents’ average performance. Some high target values result in better agent performance.

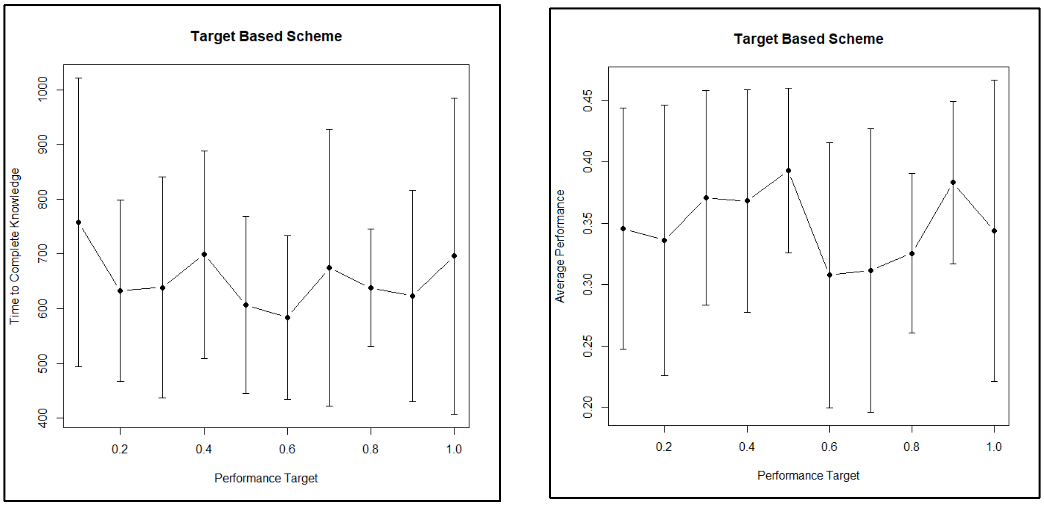

Figure 9. Knowledge efficiency based on performance target.

4.2 Knowledge Transfer Network

The agents' interaction during the simulation formed the knowledge transfer network in this study. A directed graph represents the network, where the agents become the nodes, and the edges originate from the agents who ask for knowledge. A connection between two nodes will be created if only the target agent decides to share the knowledge. Therefore, the agent interaction histories are the data source for this knowledge transfer network. As this study focused on knowledge transfer, we use in-degree edges to determine the characteristics of the network. Table 1 below specifies the properties of the knowledge transfer network for each incentive scheme based on simulations with 150 agents (*N=150*).

Table 3. Network analysis comparison between incentive schemes

Scheme	Links	Avg. Degree	Avg. Path	Diameter
Partnership	1238	8.253	2.722	6
Target-based	1301	8.673	2.655	5
Tournament-based	1174	7.827	2.844	6

There is not any significant difference between all three schemes. The number of links is the only notable attribute value among the three incentive types. It defines the number of relationships of knowledge transfer. Among all, the target-based scheme has the highest links (1301), followed by the partnership scheme (1238) and tournament-based scheme (1174). However, the average degree values are similar despite the link number differences. Each node averagely has around eight links, representing the number of partners from each agent in the simulation. A significant difference between the number of nodes and links in this network implies how closely connected the agents are. The average path and diameter of this network describe supports that idea. The simulation results show that each agent in the network can be reached within three connections, and the longest distance between agents is around six connections.

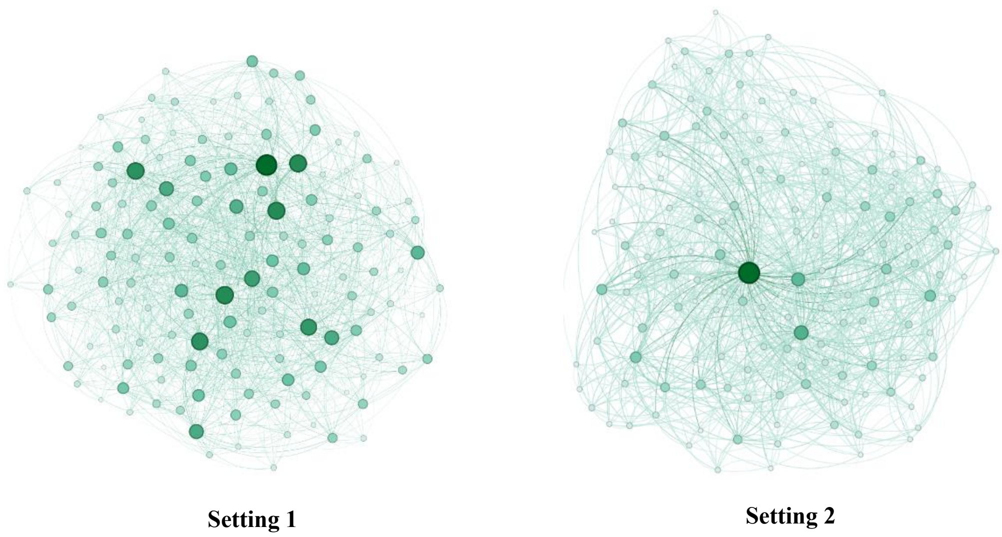

Figure 10. Knowledge transfer network based on different initial setting.

In this study, we randomly assign the agent's knowledge level in the initialization stage. An agent can have complete knowledge, half knowledge, or empty knowledge. As we set 20 knowledge fragments in all experiments, an agent with complete knowledge will have all 20 fragments, and agents with half knowledge will have ten random fragments from the beginning of the simulation. As shown in Figure 10, we begin the simulation with two different settings. Setting 1 and Setting 2 indicates the different composition of agents. In Setting 1, we randomly choose ten percent of the total agents that will be given initial knowledge fragments. Among the selected agents, we pick one that will have complete knowledge, and the rest will have half knowledge. We apply Setting 1 for partnership and target-based incentive scheme simulation. Meanwhile, in Setting 2, we randomly choose two agents that will have complete knowledge and the rest of them will not be given any initial knowledge. This setting only applies to the tournament-based incentive scheme. Therefore, the two agents selected should come from different groups to give both groups the same initial state.

The result suggests that the initial settings do not necessarily define the network structure. The number of in-degree edges determines the node size. As we only use one agent with complete knowledge, we expect the agent with complete knowledge to be the only node with many links. However, the result shows that many agents actively participate in the knowledge transfer. We can see that behaviour from the number of nodes with equal size. Setting 2 shows interesting results. Even though we set 2 agents with complete knowledge, only one shows domination in the knowledge transfer.

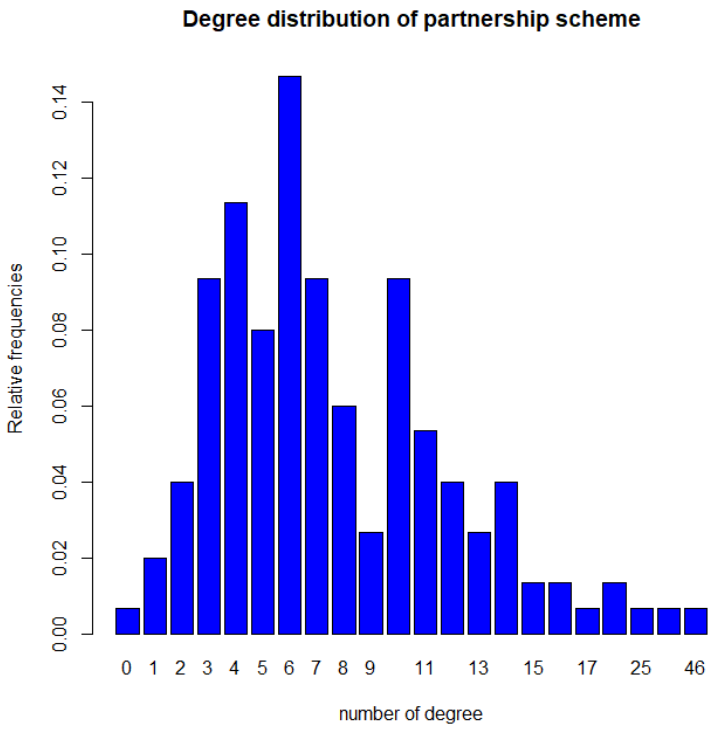

Figure 11. Degree distribution of knowledge transfer network

The network properties from all three incentive schemes suggest that the knowledge transfer network is a random network type. The type of network could be identified from the degree distribution property. One characteristic of a random network is that its degree distribution follows the binomial distribution for small-size networks (*N≈100*). The resulting network has degree distribution peaks around the average degree, as shown in Figure 11. We can also examine the randomness of the network by applying power law distribution fit. Table 2 explains how the network from each incentive scheme fits the power law distribution.

Power law distribution is well approximated by $p_k \sim k^{-\gamma}$, where p_k is the probability of any nodes having k links. Based on the exponent degree (γ), a network is categorized as a part of a random network regime if the value is greater than three ($\gamma > 3$). The network generated from the simulation results will be analyzed using the igraph R package to determine how well they fit the power law distribution. The analysis will consider three attributes to characterize fitness. *Gamma* is a numeric scalar value signifying the exponent of the power law distribution. *Xmin* is a numeric scalar value determining the minimum threshold from which the power law distribution is fitted. In other words, values smaller than xmin are regarded as outliers. The last attribute is *KS.p,* a numeric scalar value representing the p-value of the Kolmogorov-Smirnov test. The test rejected the possibility that the original data might have been derived from the fitted power-law distribution, as indicated by small p-values (less than 0.05). The bigger the *KS.p* value, the more possibility that the data follow power law distribution. The following tables show the power law distribution fit for each incentive scheme.

Table 4 Power Law Distribution Fit on Partnership Scheme

Trial	gamma	xmin	KS.p
1	3.602	10	0.36
2	3.884	10	0.73
3	3.680	10	0.08
4	3.955	10	0.24
5	3.558	10	0.59

Table 5 Power Law Distribution Fit on Target Based Scheme

Trial	gamma	xmin	KS.p
1	3.795	10	0.96
2	3.768	10	0.85
3	3.779	10	0.55
4	3.483	10	0.08
5	4.412	10	0.91

Table 6 Power Law Distribution Fit on Tournament Based Scheme

Trial	gamma	xmin	KS.p
1	4.613	10	0.99
2	4.397	10	0.98
3	3.071	10	0.49
4	3.733	10	0.25
5	3.865	10	0.94

4.3 Analysis

The simulation results suggest that organization structure (*number-of-employee* N) impacts knowledge transfer efficiency. The more significant value of N, which leads to a denser organization structure, results in a shorter time to give all the agents complete knowledge. This result aligns with previous findings (Li et al., 2021). However, the results under target-based and tournament-based settings give slightly different result. Both schemes show a positive trend in knowledge efficiency up to a certain point. Then, the knowledge efficiency starts to decrease after reaching that point. This finding might suggest the correlation between organization size and perceived incentive. As we focus on group-based incentives, the number of people significantly determines the total benefit shared among the members. The more people in the organization, the more risk the members should face because they should perform well as a group but cannot control others' behavior.

Besides organization structure, knowledge complexity also affects the efficiency of knowledge transfer. As this study follows the combination rule instead of the addition rule to represent knowledge accumulation, the knowledge gets more complex along with the large value of the *knowledge-fraction* variable. The simulation results show that the time needed becomes longer when the knowledge has more fractions. These results are consistent throughout all three incentive schemes. Interestingly, a few adjustments in the *tolerance-level* and *max-vision-range* variable do not significantly change the time needed to give all agents complete knowledge. Even though other trials show that *tolerance-level* and *max-vision-range* affect knowledge transfer positively, they do not apply to the case where knowledge complexity is varied. One possible explanation for this finding is that the agent's intrinsic motivation alone is insufficient to improve knowledge transfer efficiency. Other external factors should exist, such as the community structure (Guechtouli et al., 2013*)*. The simulation results show that the network structure formed due to knowledge transfer has similar shapes. Therefore, the community structure is always the same even though the tolerance level and knowledge vision vary.

Regarding the first research question related to the natural form of knowledge transfer network, we assume that the interaction history between agents will generate a scale-free network. This study provides initial settings that enable preferential attachment by giving agents different levels of knowledge. The expected result is that most knowledge exchange interactions will concentrate on the few nodes with higher knowledge at the beginning of the simulation. However, the knowledge transfer networks constructed from agent interactions show opposite results. Instead of focusing on some nodes, the knowledge exchange happened equally between many nodes, making the network structure resemble a random network.

The formation of a random network instead of a scale-free network could happen because the agents' objective is to collect knowledge as quickly as possible and can freely interact with any agents around them. Agents do not need to consider how much knowledge their partner has. The knowledge exchange will happen as long as their partner has the necessary knowledge. The result may be different if there are restrictions. For example, agents can only share with other agents with similar knowledge levels. Therefore, the simulation result does not support Hypothesis 1 of this study. This research shows that knowledge transfer networks will resemble a random network as shown in Table 6.

Table 7 Power Law Distribution Fit Without Incentives

Trial	gamma	xmin	KS.p
1	4.300	10	0.49
2	3.952	10	0.63
3	3.837	10	0.24
4	3.885	10	0.99
5	3.956	10	0.18

As for the second research question related to the effect of applying an incentive mechanism, we assume that incentives will stimulate a higher possibility of sharing, which results in more link formation. As shown in Table 2, there is a slight improvement, but it is insufficient to change the status of the whole network. This small improvement probably happens because the model includes intrinsic motivation by default. Knowledge transfer occurs as the agents want to complete their knowledge collection. In this case, agents will only exchange knowledge if their partner has the needed knowledge. Thus, extrinsic motivation (group-based incentives) cannot outweigh the effect of intrinsic motivation (the desire to have complete knowledge).

This finding is aligned with previous studies (Jewels & Ford, 2006), which found that external incentives do not impact knowledge sharing significantly. Moreover, it reflects the general view of literature that knowledge workers will unlikely be motivated by extrinsic rewards. Therefore, the simulation result supports Hypothesis 2 of this study. This research shows that applying group-based incentive schemes on knowledge transfer within organizations has a positive outcome regarding the number of participations in the knowledge transfer activity.

Chapter 5.　Conclusion

5.1 Summary of the Study

This research defines the knowledge transfer network topology and examines the impact of group-based incentives on the efficiency of knowledge transfer and network structure change.

The fundamental theories of knowledge transfer are outlined in Chapter 2, which also examines how incentive mechanisms and other forms of external motivation can impact the effectiveness of information transfer. To clarify how knowledge transfer occurs and what elements will impact that process, it first summarizes the idea of knowledge exchange and diffusion. The review's findings characterize knowledge transfer and its relationship with human behavior. It then looks at some earlier research on incentive mechanisms and how knowledge transfer scenarios can use them. Additionally, prior simulation models are examined, including the description of agents and simulation methodologies, to build a simulation model for knowledge transfer observation.

The construction of the simulation's agent-based model is described in Chapter 3. This work adapts a comparable agent description based on what is known from earlier studies. All agents' characteristics and actions adhere to the definition of the commonly used model for a knowledge transfer network. The study then goes into detail about how incentive mechanisms shape agents' perceptions of knowledge transfer. The model is going through the verification and validation procedure before moving on to the simulation experiments. Software project testing common practice is used for the verification process. This study uses input validation, face macro validation, and face micro validation as part of the validation process.

The impact of various variable settings on the effectiveness of knowledge transfer is examined in Chapter 4. Sensitivity analysis is used to determine how each variable affects the output value. We next move on to the simulation using the optimum value discovered during the sensitivity testing. Three separate scenarios—partnership scheme, target-based scheme, and tournament-based scheme—are used to perform the simulation. Each scenario is run multiple times following the best practices of agent-based simulation, and the outcomes are then presented.

Based on the simulation's findings, it is determined that applying an incentive mechanism has little effect on the structure of the knowledge transfer network. The interaction between agents throughout the knowledge transfer process results in the formation of a random network, even though the simulation uses varied initial values for the knowledge level of the agents. Because agents can engage freely and have only one objective, gathering all knowledge, there is no preference attachment. As a result, the simulation's findings do not confirm the primary hypothesis that knowledge transfer occurs via a scale-free network.

5.2 Implications

This research contributes to the area by examining the impact of group-based incentive mechanisms on the structure of knowledge transfer networks. The first step in this research is to define a decision model that characterizes how agents view the likelihood that their engagement in knowledge transfer will result in external benefits. Prior studies mainly considered internal factors when modeling knowledge transfer and rarely discussed incentive mechanisms. Second, this research focuses on how the agents make connections. In contrast, earlier studies solely focused on the effectiveness or efficiency of knowledge transfer and had already specified the links between agents.

Traditional network study has concentrated on the constraints actors face due to their network positions and has assumed that network architecture is static. Organizations typically have a star-shaped organizational structure with a very hierarchical degree of centrality, with the most sought-after knowledge provider at the center. These agents serve as the initial sources of knowledge. The congestion effect makes it difficult for knowledge to spread within an organization with a star-shaped structure. The congestion happens because knowledge seekers know each community member's unique competencies. Given their goal to have complete knowledge, agents will simultaneously ask the most qualified agent, resulting in a queueing phenomenon.

The principle of star-shaped is evident in real-world observations. In a company, employees usually build social relationships and transfer knowledge based on organizational hierarchy. Employees interact with their supervisors more frequently because they need access to information related to their tasks. They rarely interact with their peers because it is more likely that people in higher positions are more qualified and have access to more information. Asking peer employees comes with uncertainties that can be time-consuming. As a result, they prefer waiting for answers from supervisors to actively seeking knowledge from their peers. This behavior constrained the spread of knowledge because only a few people were involved in the knowledge transfer interaction. However, the manager's manipulation could widen the knowledge spread.

Any link addition between any two nodes will result in the growth of knowledge and value under the influence of exchange mechanisms. However, the high-level network members' knowledge development rates accelerate and are more significant than typical network members. The unbalanced growth rate causes the "knowledge gap" phenomenon. Therefore, to enhance each person's average knowledge level, the network manager must implement administrative or economic measures to share the growth evenly. An incentive mechanism is one example of economic measures to overcome the knowledge gap problem.

Following the maximum profits theory, network members look for initial and subsequent connections. Typical members of equal status will connect and form more triads due to connecting with a high-value member. Network gathering appears at the same time that the average shortest distance declines. Even though the evolution takes place as self-organization without managerial interference, a manager's manipulation could quicken the process. In this case, the incentive mechanism is the accelerator for that process. This study found that the knowledge transfer network has more links under the incentive mechanism compared to the no-incentive situation. A network with more links and a small diameter will better spread knowledge across the organization.

However, instead of solely concentrating on designing incentive strategies, it may be necessary to better align individuals with the goals of their project team, the goals of their organization, or the rules and regulations of their professional discipline to encourage them to share their knowledge and experiences. This practice may give those who want to promote knowledge sharing the chance to look at the problem from several angles. To better predict people's attitudes toward knowledge sharing, it is crucial to understand how they may fit with those three institutional elements.

The simulation results imply that larger organizations provide a shorter period to produce agents with perfect knowledge. However, it is debatable to say that the organization must be bigger. The simulation results show that once there are more than 150 members, the improvement in knowledge transfer dependent upon growing the organization size is less significant than when there are less than 150 members. Additionally, overextending the organization will inevitably burden the management with higher labor costs, and the scientific size of an organization also depends on the kind and subject of interactions between the members. Therefore, the management can exert little effort to increase the organization's size after reaching roughly 150 members.

5.3 Limitations and Future Studies

The following limitations of this study on knowledge transfer and group-based incentives inside the company can be addressed in follow-up research. The major limitation of this study is its general assumption that agents can interact with any other agents. That assumption does not adequately represent the hierarchical structure that typically exists inside an organization. Organizations with strict knowledge transfer policies would adopt a star-shaped organizational structure, with the original, highly knowledgeable agents in the center as the most sought-after knowledge providers (Guechtouli et al., 2013). The only aspect of organizational hierarchy in this study is the knowledge level at the beginning of the simulation. Future research could expand the model's interaction rules to overcome this restriction.

Agents are developed with the ability to explore the environment and evaluate all opportunities when looking for new partners in the model because of the research goals and simplification purposes. They know precisely where they can obtain the necessary knowledge. However, agents inside and outside organizations are not perfectly rational. We suggest extending the models presented in this work by integrating bounded rationality while developing partnerships in the following studies.

This study does not account for weight in the utility function of the model. In the utility calculation, Li (2021) assigns random weight values to represent various facets of individual personality inside an organization. Future research should use an experimental design to give agents precise values to reflect different meanings.

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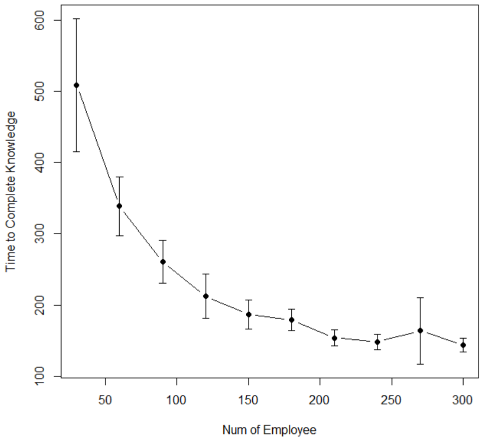
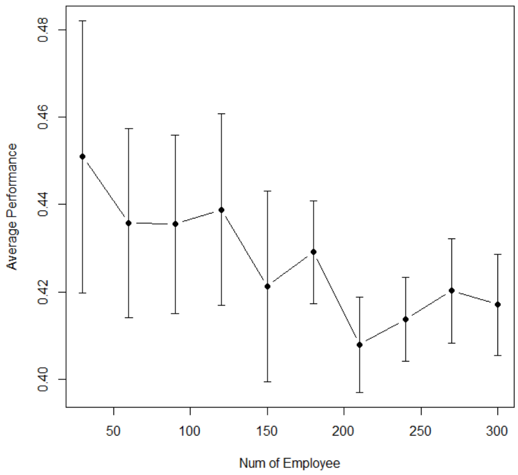
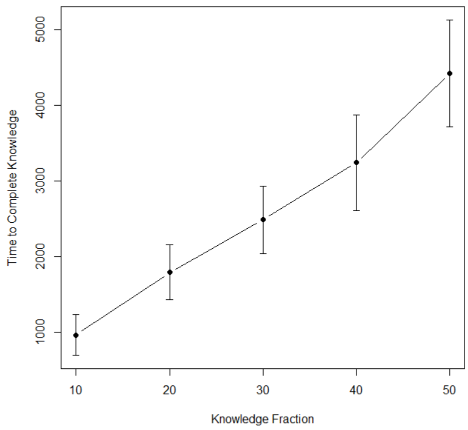
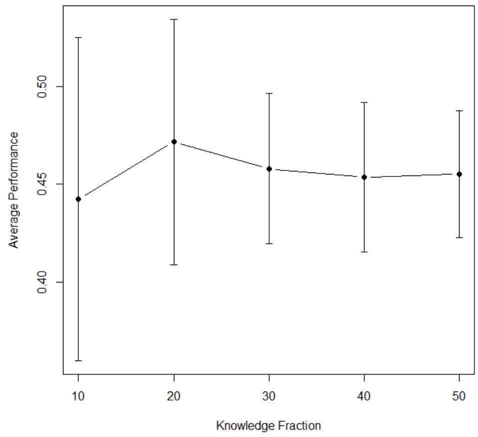
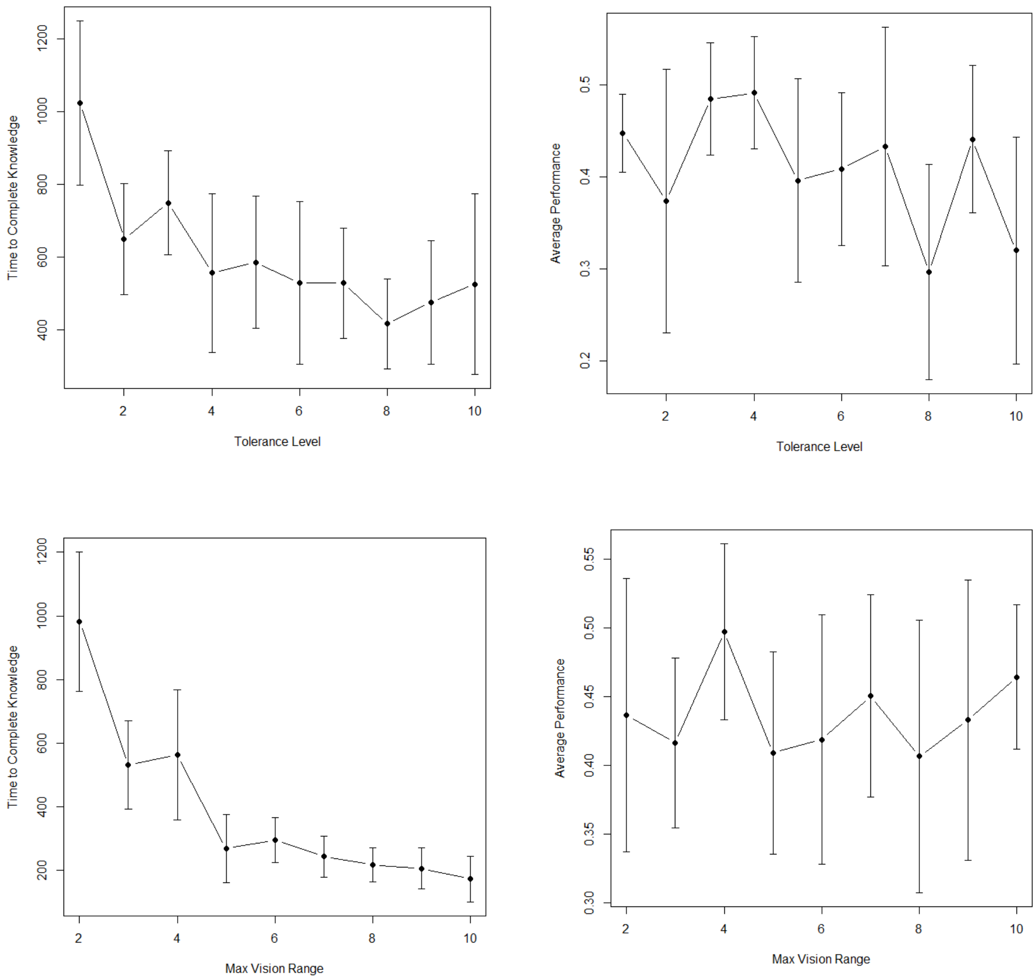
Appendix 1: Input Validation Results










Time to Complete Knowledge
Tolerance Level
Average Performance
Tolerance Level
Time to Complete Knowledge
Max Vision Range
Average Performance
Max Vision Range

Abstract (Korean)

지식 이전은 조직의 성장과 지속 가능성에 중요한 역할을 한다. 조직은 이 활동을 통해 지식 손실을 방지하고 혁신을 촉진할 수 있다. 또한, 지식에 대한 접근성은 다른 사람들이 이미 저지른 과거의 실수를 기록하여 향후 동일한 실수가 반복되지 않도록 하기 때문에 실수를 줄일 수 있다. 또한 지식 이전은 조직원들이 함께 일하고 아이디어를 공유할 수 있는 기회를 만들어 전문성 개발에 도움이 된다. 조직은 지식을 적절히 유지해야 급변하는 환경에서도 지속적으로 혁신하고 개선하며 경쟁할 수 있다. 하지만 합리적인 개인은 지식 이전을 통해 얻을 수 있는 이익이 비용을 초과할 때만 지식 이전에 참여하는 경향이 있다.

인센티브는 사람들의 성과에 동기를 부여한다. 인센티브에는 여러 유형이 있지만 이 연구에서는 물질적 인센티브에 초점을 맞추었다. 물질적 인센티브는 급여부터 보상 패키지 또는 스톡옵션 프로그램까지 다양하다. 개인은 지식을 독점하려는 경향이 있기 때문에 인센티브 메커니즘은 이러한 욕구를 완화하는 한 가지 요인이 될 수 있다. 이 연구는 인센티브 메커니즘이 지식 이전 활동에 미치는 영향을 분석하는 것을 목표로 한다.

인센티브는 사람들의 성과에 동기를 부여한다. 인센티브에는 여러 유형이 있지만 이 연구에서는 물질적 인센티브에 초점을 맞추었다. 물질적 인센티브는 급여부터 보상 패키지 또는 스톡옵션 프로그램까지 다양하다. 개인은 지식을 독점하려는 경향이 있기 때문에 인센티브 메커니즘은 이러한 욕구를 완화하는 한 가지 요인이 될 수 있다. 이 연구는 인센티브 메커니즘이 지식 이전 활동에 미치는 영향을 분석하는 것을 목표로 한다.

이 결과는 인센티브 메커니즘이 지식 전달 효율성과 양의 상관관계가 있음을 시사한다. 그러나 네트워크 구조를 바꾸기에는 그 효과가 크지 않다. 이 결과는 조직 관행에 대한 귀중한 인사이트를 제공한다. 관리자는 양이 아닌 사람의 질에 초점을 맞추고 지식 이전 활동에 참여하도록 동기를 부여할 수 있는 다른 요인을 제시할 필요가 있다.

주요어 : 지식 이전, 인센티브 메커니즘, 에이전트 기반 모델, 네트워크 구조
학 번 : 2021-23952