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EFFECTS OF NETWORK SIZE ON KNOWLEDGE ACQUISITION VIA E-LEARNING COMMUNITY

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Abstract. *The purpose of this paper is to research the effects of network size on knowledge acquisition via E-Learning community by virtual experiment. Key factors of knowledge acquisition via E-Learning are identified, including knowledge acquisition bases, knowledge acquisition performance and knowledge acquisition targets; then based on multi agent modeling idea, computational models are constructed for these key factors; corresponding experiment simulations are implemented by NetLog in order to research macro characteristics emerged by interaction of individuals in micro level of E-Learning knowledge community. According to experiment results, explicit insights are given into how network size influences key factors of knowledge acquisition via E-Learning. Research results can help knowledge community focus on the implication of network size on knowledge acquisition, so that the appropriate strategy can be adopted to achieve E-Learning goals.*
Keywords: Network size, Knowledge community, E-Learning, Simulation, Netlog

1. **Introduction.** E-Learning has been regarded as a fast growing research and application area with huge market potential. It may become an essential corporate strategy to connect with the rapid development of knowledge communities surrounding E-Learning in the process of promoting knowledge management.

Knowledge acquisition is the desired outcome of E-Learning; hopefully knowledge innovation can be promoted through the learning of an organization, the sharing of knowledge, and the creating of a knowledge community [1]. As a social network community (SNC), E-Learning community is a social structure made of nodes that are tied by one or more specific types of interdependent people.

In recent years great attention has been concentrated on the relationship between behavioral patterns of knowledge acquisition and features of network organizations [2-4].

Taking size as a moderator for the relationships between constructs [5], one representative study found knowledge flow is positively related with the connectedness of organizations [6,7] (Uzzi and Gillespie, 2002; Uzzi and Lancaster, 2003). Simulation experiment was used to explore the interdependence of knowledge flow and dynamic behavior patterns of network-based organization. It was disclosed the larger the network organization, the greater number of the neighbor nodes one organization has, and the higher the proportion of nodes that will change their knowledge state [8].

On basis of cognitive psychology and social psychology, the other research streams, focusing on the relationships of learning, the absorptive capability and effectiveness of knowledge flow [9] (Loasby, 2001), found individuals with larger networks are less emotionally close to each member of their network, and the emotional intensity of each relationship in the network – smaller networks tend to contain fewer individuals but at a higher level of emotional closeness than large networks [10,11].

Recently, to focus on the building and verifying of online social networks for knowledge acquisition, Social Network Service (SNS) oriented knowledge community has been becoming the base for E-Learning. Thus, understanding key factors of knowledge acquisition via E-Learning of SNS oriented knowledge community and the relationship between key factors and network feature are important for at least three reasons.

First, SNSs are believed to reflect real-life relationships of people more accurately and more innate to human cultural experience. SNS oriented knowledge communities are useful in the sense that they convene people with similar skills and interests who engage in informal interaction, support one another and give meaningful advice and feedback regarding tasks and topics of shared interest. Therefore, benefits from an efficient SNS oriented knowledge community for E-Learning that can be brought to an organization environment include: learning curve improvement; quick response and efficient customer satisfaction (QR/ECS); increased experience sharing within an organization; a decrease in repetitive work, enhanced communication and innovation; efficient resolution of practical problems; and increased learning overall in relevant areas of growth [5].

Second, although most research indicates the relationship between knowledge flow and social features in network organization, research in modeling knowledge acquisition via E-Learning community has remained sparse. Moreover, previous study demonstrates that network size is an important network feature for better knowledge flow; consequently there may be a trade-off network size in the network organization. Following the same logic, we predict that effects of network size on knowledge acquisition via E-Learning vary with network scale.

Further, as the emergent behaviors that come from the interaction of individuals, groups and teams have the characteristics of complexity, dynamics, adaptation and nonlinearity, it is almost impossible to accurately collect primary data on the evolution of network organizations [12] (Carley, 1996). Most researches use valid questionnaires to find whether network size has significant effects on the learning intention and learning performance. However, this results in a significant amount of neglect of the links between micro-macro behaviors and macro-dynamics features in the network organization.

Hence, our study seeks to advance our understanding of key factors behind efficient knowledge acquisition via E-Learning and explore the effects of network size. We bring together theories of E-Learning to examine key factors leading to efficient knowledge acquisition in SNS oriented knowledge community. Our computational models build on these theories to predict how network size influences these key factors. Next we conduct a virtual experiment to identify macro characteristics of knowledge acquisition via E-Learning emerged by interaction of individuals in micro level. And such an effort is made in order to answer the following research questions:

(1) Will key factors of knowledge acquisition via E-Learning change over time in response to varying network size in knowledge community?

(2) If it does, how do they change differently?

The rest of this paper is organized as follows. Section 2 presents the research framework. Then the research design is built in Section 3. In Section 4 experiment results are analyzed to acquire more insights of the study. Finally, Section 5 gives a brief conclusion and provides some possible future research directions.

2. **Research Frameworks.** Based on these questions, research framework is illustrated as Figure 1. Firstly, knowledge acquisition via E-Learning in SNS oriented knowledge community is proposed to be influenced by varying network size. Secondly, key factors of knowledge acquisition via E-Learning are identified as variables in following computational models. Thirdly, computational models are constructed for virtual experiment to explore the effects of network size according to setting evolution rules. Fourthly, experiment results as feedbacks are analyzed to give insight of appropriate strategy for achieving objectives of knowledge acquisition via E-Learning.

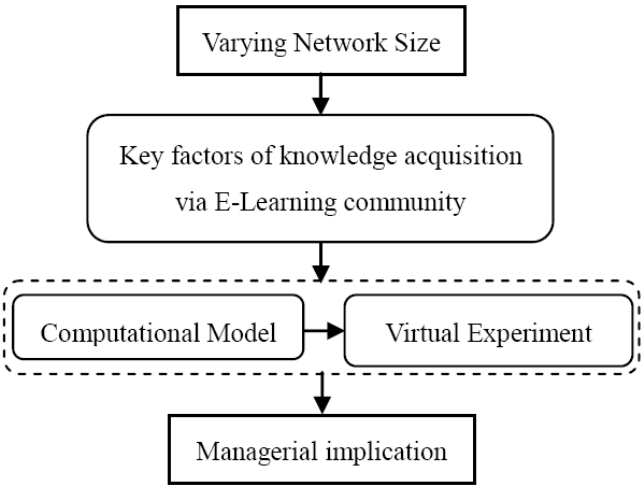

FIGURE 1. Framework for network size analysis

2.1. **Key factors of knowledge acquisition via E-Learning community.** Critical successful factors [13] for knowledge acquisition via E-Learning community can be classified into bases, targets and performance as shown in Figure 2 [14,15].

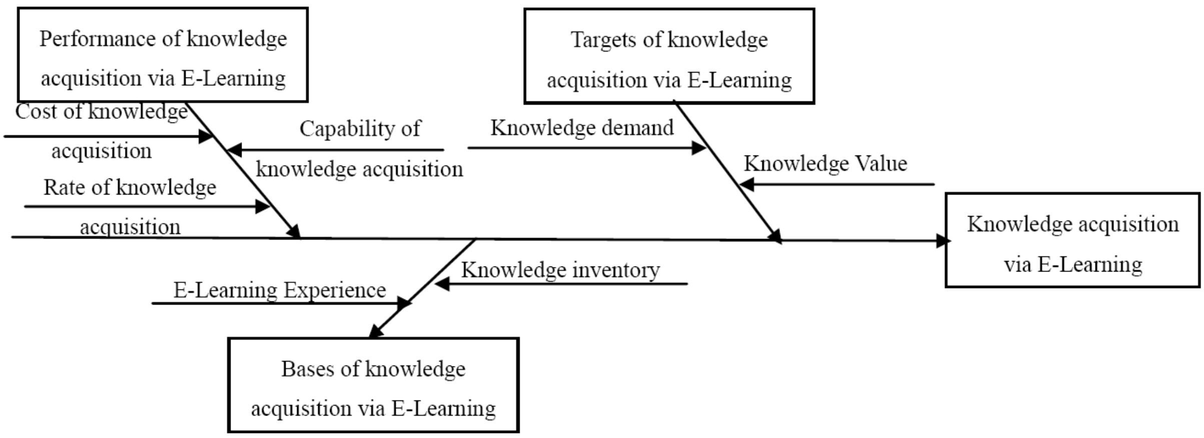

FIGURE 2. Key factors of knowledge acquisition via E-Learning

Knowledge inventory and E-Learning experience are closely tied to bases of knowledge acquisition via E-Learning, since people who have been successful in E-Learning in the past are typically more motivated to engage in E-Learning in the future [16].

To meet the knowledge demand and nurture a corporate culture based on knowledge sharing should be goals of knowledge acquisition via E-Learning; as a result knowledge demand and the corresponding knowledge value are set as target metrics.

The desired outcome for knowledge acquisition via E-Learning should hasten the collaborative climate of the knowledge community, such as higher intellectual capital, organizational creativity, innovative business models, and the overall company value and efficiency. Therefore, knowledge acquisition cost, knowledge acquisition capability and knowledge acquisition rate are taken as performance key factors.

2.2. **Computational model.**

2.2.1. *Knowledge acquisition bases.*

(1) Knowledge inventory

In each knowledge dimension of the organization, knowledge inventory is composed of knowledge and skills of all employees. According to the individual mental model, knowledge of the people can be deepened and extended by motivating factors [18], such as environment and events. Then the organization can produce new ideas and insights during the procedure of knowledge absorption and application.

As a result, knowledge inventory of the organization at time t has close relationship with initial knowledge inventory, knowledge gap, E-Learning experience, knowledge gains and network size at time $t-1$, as shown in Equation (1).

$$KwInventory_t = f(kwInventory_0, kwGap_{t-1}, lExperience_{t-1}, kwGains_{t-1}, NSize_{t-1}) \tag{1}$$

where:

$kwInventory_o$ = Initial knowledge inventory

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

$lExperience_{t-1}$ = E-Learning experience at time $t-1$

$kwGains_{t-1} = kwValue_{t-1} - kwCost_{t-1}$ = knowledge gains from knowledge value at a cost at time $t-1$

$NSize_{t-1}$ = network size at time $t-1$

(2) E-Learning experience

The development of organization's competencies evolves with time by characteristics of path dependent. In addition, organization's competencies acquiring by learning greatly depend on previous E-Learning experience [4], which has positive effects on knowledge innovation capability of the organization.

Thus, E-Learning experience of the organization at time t has close relationship with initial E-Learning experience, network size, knowledge gap and gains at time $t-1$, as shown in Equation (2).

$$Experience_t = f(Experience_0, Experience_{t-1}, NSize_{t-1}, kwGap_{t-1}, kwGains_{t-1}) \tag{2}$$

where:

$Experience_0$ = initial E-Learning experience

$Experience_{t-1}$ = E-Learning experience at time $t-1$

$NSize_{t-1}$ = network size at time $t-1$

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

$kwGains_{t-1} = kwValue_{t-1} - kwCost_{t-1}$ = knowledge gains from knowledge value at some cost at time $t-1$

2.2.2. *Knowledge acquisition performance.*

(1) Knowledge acquisition rate

Knowledge acquisition rate can be used to describe the velocity of the organization to acquire knowledge [19]; therefore, it is closely tied to E-Learning experience and knowledge gap, as shown in Equation (3).

$$kwRate_t = f(kwGap_{t-1}, Experience_{t-1}) \tag{3}$$

where:

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

$Experience_{t-1}$ = E-Learning experience at time $t-1$

(2) Knowledge acquisition cost

As costs are definitely involved in the procedure of knowledge acquisition via E-Learning [20], knowledge acquisition cost is closely tied to knowledge gap and knowledge acquisition rate, as shown in Equation (4).

$$KwCost_t = f(kwRate_{t-1}, kwGap_{t-1}) \tag{4}$$

where:

$kwRate_t$ = knowledge acquisition rate at time t

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

(3) Knowledge acquisition capability

Knowledge acquisition capability via E-Learning reflects knowledge gains with certain rate at some cost [21], as shown in Equation (5).

$$KwCapability_t = f(kwRate_{t-1}, kwGains_{t-1}) \tag{5}$$

where:

$kwRate_{t-1}$ = knowledge acquisition rate at time $t-1$

$kwGains_{t-1} = kwValue_{t-1} - kwCost_{t-1}$ = knowledge gains at time $t-1$

2.2.3. *Knowledge acquisition targets.*

(1) Knowledge acquisition demand

As a new knowledge service, SNS oriented knowledge community for E-Learning can help problem solving by refining knowledge from all explicit and tacit information resources, then knowledge should be customized according to demand [22].

Consequently, knowledge demand of the organization at time t is closely related to initial knowledge demand, knowledge gap, E-Learning experience and knowledge acquisition rate at time $t-1$, as shown in Equation (6).

$$KwDemand_t = f(kwDemand_0, kwGap_{t-1}, Experience_{t-1}, kwRate_{t-1}) \tag{6}$$

where:

$kwDemand_0$ = initial knowledge demand

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

$Experience_{t-1}$ = E-Learning experience at time $t-1$

$kwRate_{t-1}$ = knowledge acquisition rate at time $t-1$

(2) Knowledge value

As life cycle is one of the important characteristics of knowledge, knowledge value [23] is closely related to initial knowledge value and knowledge gap, as shown in Equation (7).

$$KwValue_{t-1} = f(kwValue_0, kwValue_{t-1}, kwGap_{t-1}) \tag{7}$$

where:

$kwValue_0$ = initial knowledge acquisition value

$kwValue_{t-1}$ = knowledge acquisition value at time $t-1$

$kwGap_{t-1} = kwDemand_{t-1} - kwInventory_{t-1}$ = knowledge gap between knowledge demand and knowledge inventory at time $t-1$

2.3. Virtual experiment. In order to enhance understanding of complex behavior of human organization, computational techniques can be used [24] (Hanneman, 1995). In this field, virtual experiment takes many advantages of analyzing organizational phenomena through mathematical models in the following reasons.

First, it is nearly impossible to observe the behaviors, the rules and routines of various nodes in actual network organizations. Longitudinal data about network organizations provide less useful and practical information about the micro-processes of network organizations than that might be expected.

Second, groups or organizations need to observe their environment and to make their decisions based on the transmitted information. Accordingly simulation methods can help us have a deep understanding of key problems faced by network organizations, e.g., learning, selection and adaptation.

Moreover, the virtual experiment provides us unique perspectives on how individuals respond and how emergent patterns will appear under the uncertainty and ambiguity condition.

From these perspectives, virtual experiment provides us with a useful tool to explore the flexible adaptation of network organization and which, in turn, helps us to understand the emergent behavior of network organizations in the process of complex interaction. Thus, we use the virtual experiment in the following research design of our study.

3. Research Design. Guided by research framework and previous literature, a specific research design is composed to address the research questions adequately. In the following section, we will introduce NetLogo and then describe the evolution rules in the virtual experiment.

3.1. NetLogo. NetLogo is a programmable modeling environment, especially suitable for modeling complex system evolving over time [25]. Thousands of independent agents in NetLogo can be instructed by modelers; therefore, it becomes possible to research macro-level model emerging as the interaction results of micro-level. In this study, the simulation procedure by NetLogo is shown in Figure 3. The simulation is used to explore the effects of network size on key factors of knowledge acquisition via E-Learning with 1000 simulation times and 100 fit iteration times.

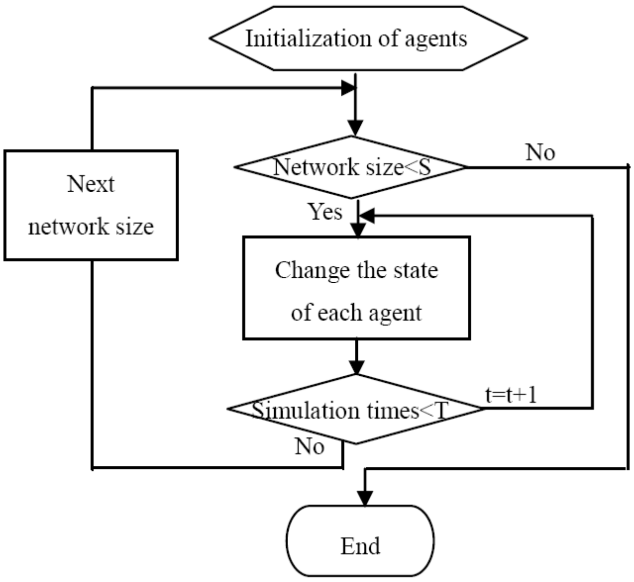

FIGURE 3. Procedure of simulation

3.2. **Evolution rules for virtual experiment.**

3.2.1. *Initialization of agents.* Network size is valued from 100 to 1000 with step of 100. To ensure the general characteristics of E-Learning community [15], random float function is used to reflect the initial vale of knowledge inventory, E-Learning experience, knowledge demand, and knowledge value of each agent, as shown in Equations (8)-(11).

$$KwInventory_{i,0} = random - float(10) \tag{8}$$

$$Experience_{i,0} = random - float(10) \tag{9}$$

$$KwDemand_{i,0} = random - float(10) \tag{10}$$

$$KwValue_{i,0} = random - float(10) \tag{11}$$

3.2.2. *Evolution rules for key factors.* Concerning different E-Learning characteristics of each agent [14], evolution rules of each agent for knowledge inventory, E-Learning experience and knowledge demand with given initial value are denoted by random float function, as shown in Equations (12)-(14).

$$KwInventory_{i,t} = random - float(kwInventory_{i,0} + kwInventory_{i,t-1}) \tag{12}$$

$$Experience_{i,t} = random - float(Experience_{i,0} + Experience_{i,t-1}) \tag{13}$$

$$KwDemand_{i,t} = random - float(kwDemand_{i,0} + kwDemand_{i,t-1}) \tag{14}$$

According to Equations (3)-(6) and (7), knowledge gap is the driven for knowledge acquisition via E-learning community; therefore, evolution rules for knowledge value [23], knowledge acquisition rate, knowledge acquisition cost and knowledge acquisition capability [21] can be clearly indicated as Equations (15)-(18).

$$KwValue_{i,t-1} = kwValue_{i,0} - kwValue_{i,t-1} * \exp\left(\frac{-kwGap_{i,t-1}}{kwValue_{i,t-1}}\right) \tag{15}$$

$$kwRate_{i,t-1} = \lambda_1 * kwGap_{i,t-1} + \lambda_2 * Experience_{i,t-1} \tag{16}$$

$$kwCost_{i,t-1} = \begin{cases} 0 & kwGap_{i,t-1} \leq 0 \\ c_1 * \frac{kwGap_{i,t-1}}{kwRate_{i,t-1}} & kwGap_{i,t-1} > 0 \end{cases} \tag{17}$$

$$kwCapability_{i,t-1} = \begin{cases} 0 & kwGain_{i,t-1} \leq 0 \\ c_2 * kwRate_{i,t-1} * kwGain_{i,t-1} & kwGain_{i,t-1} > 0 \end{cases} \tag{18}$$

where:

$KwGap_{i,t-1} = kwDemand_{i,t-1} - kwInventory_{i,t-1}$ = knowledge gap between knowledge demand and inventory at time $t-1$

$\lambda_1, \lambda_2, c_1, c_2 = random - float(10)$ = parameters for knowledge acquisition rate, knowledge acquisition cost and knowledge acquisition capability

4. **Experiment Results.**

4.1. **Effects of network size on knowledge acquisition bases.**

4.1.1. *Effects of network size on knowledge inventory.* From Figure 4, it can be seen that knowledge inventory increased with network size to reach maximum when $NSize = 600$, then decreased and remained little change when $NSize > 800$.

It shows E-Learning is a gradual process. Knowledge inventory can increase with network size as a result of having more knowledge resources; however, after a threshold of network size, knowledge inventory of the E-Learning community becomes saturated, which demonstrates limited effects of network size on knowledge inventory.

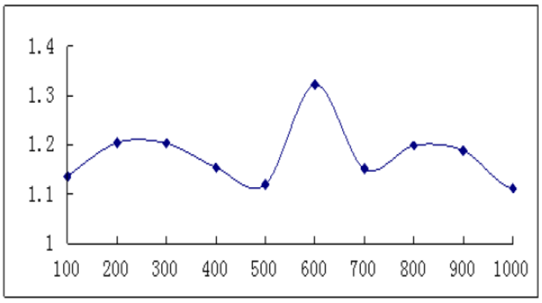

FIGURE 4. Effects of network size on knowledge inventory

4.1.2. *Effects of network size on E-Learning experience.* Although more participants are involved in E-Learning community, overall E-Learning experience has no significant correlation with network size as shown in Figure 5.

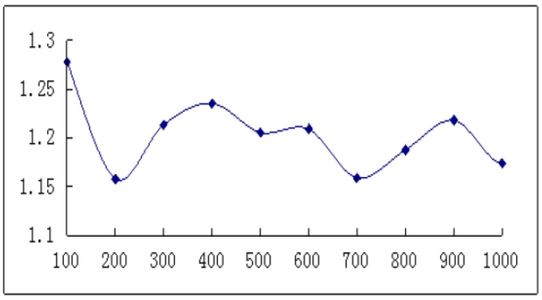

FIGURE 5. Effects of network size on E-Learning experience

This tendency illustrates that network size has little influence on E-Learning experience, since the most important motivational factor for E-Learning is past learning performance and the feeling of mastering a task or a discipline [14].

4.2. Effects of network size on knowledge acquisition performance.

4.2.1. *Effects of network size on knowledge acquisition rate.* As knowledge acquisition rate has close relationship with knowledge inventory, similar tendency appeared in Figure 6 as that in Figure 4, i.e., knowledge acquisition rate increased gradually with network size to reach maximum when $NSize = 500$, then it decreased and remained little change when $NSize > 800$.

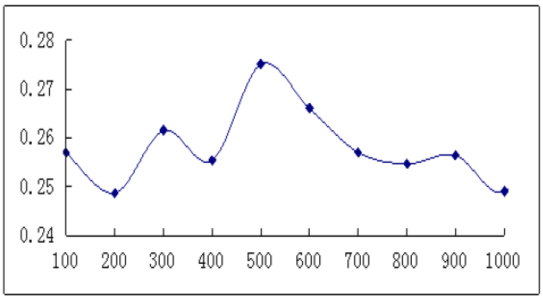

FIGURE 6. Effects of network size on knowledge acquisition rate

This tendency may happen as a result of redundant communications caused by increasing network size in E-Learning community, and consequently knowledge acquisition rate is retarded.

4.2.2. *Effects of network size on knowledge acquisition cost.* Knowledge acquisition cost increased with network size to reach maximum when $NSize = 400$, then decreased sharply when $NSize > 400$; however, this descending trend disappeared when $NSize \geq 800$, as shown in Figure 7.

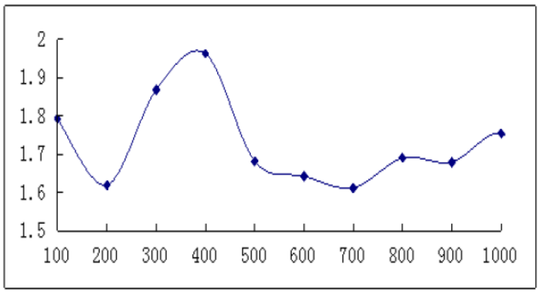

FIGURE 7. Effects of network size on knowledge acquisition cost

The descending trend of knowledge acquisition cost happens as a result of network scale effect; in contrast the reversed tendency appears due to oversized network scale or vice versa.

4.2.3. *Effects of network size on knowledge acquisition capability.* As shown in Figure 8 knowledge acquisition capability increased with network size when $400 \leq NSize < 600$, reaching maximum when $NSize = 600$, while declination tendency existed when $NSize < 400$ or $NSize > 600$.

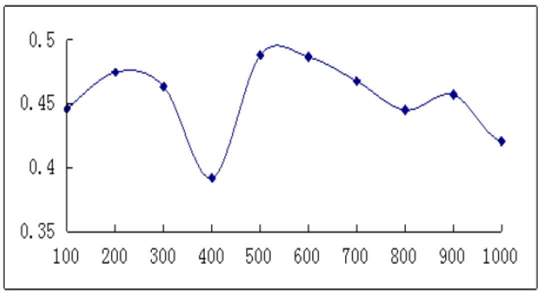

FIGURE 8. Effects of network size on knowledge acquisition capability

With the development of knowledge community, knowledge acquisition capability can increase with network size and reach maximum with definite tendency. However, since knowledge acquisition capability is closely tied to knowledge acquisition cost, its decrease tendency appears while knowledge acquisition cost increases.

4.3. **Effects of network size on knowledge acquisition targets.**

4.3.1. *Effects of network size on responsiveness of knowledge demand.* Responsiveness of knowledge demand has fluctuant relationship with network size before reaching maximum when $NSize = 600$, and meanwhile the decline tendency apparently appeared when $NSize > 600$, as shown in Figure 9.

This tendency obviously shows specific characteristics relating to the evolutional behavior of participants in the E-Learning community, because each people has the individualized knowledge domain.

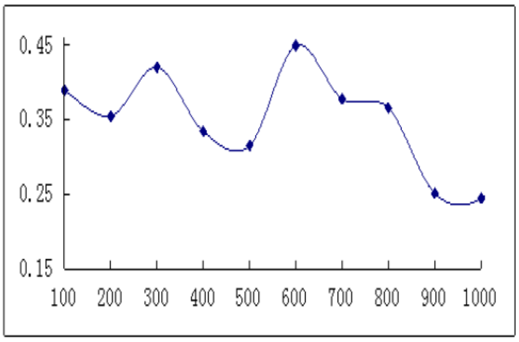

FIGURE 9. Effects of network size on responsiveness of knowledge demand

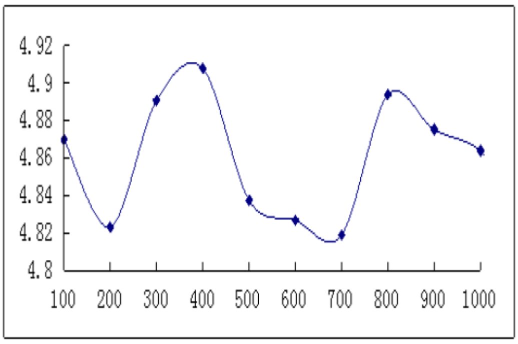

FIGURE 10. Effects of network size on of knowledge acquisition value

4.3.2. *Effects of network size on knowledge acquisition value.* Knowledge value had no significant correlation relationship with network size, reaching maximum when $NSize = 400$ while decreasing minimum when $NSize = 700$, as shown in Figure 10.

According to the evolution rule, knowledge value depends on knowledge gap in exponential decay way; thus, fluctuation tendency appears accordingly. And knowledge value can fully be achieved within a certain network size.

5. Managerial Implications and Concluding Remarks. The experiment results are summarized in Table 1.

TABLE 1. Simulation results

Effect of network size	Network size	Key factors
Positive effect	$NSize \leq 600$	Knowledge inventory
		Knowledge demand
	$NSize \leq 400$	Knowledge acquisition cost
	$NSize \leq 500$	Knowledge acquisition rate
	$400 < NSize \leq 600$	Knowledge acquisition capability
Negative effect	$600 < NSize \leq 1000$	Knowledge inventory
		Knowledge demand
	$400 < NSize \leq 800$	Knowledge acquisition cost
	$500 < NSize \leq 1000$	Knowledge acquisition rate
	$NSize <= 400$ or $600 < NSize \leq 1000$	Knowledge acquisition capability
No significant effect	$800 < NSize \leq 1000$	Knowledge acquisition cost
	All network size	E-Learning experience
		Knowledge value

Based upon these findings, we state two implications of this study as below.

First, our study contributes to additional virtual experiment that network size can influence key factors of knowledge acquisition via E-Learning in SNS oriented knowledge community. Moreover, network size works on key factors of knowledge acquisition in different ways. In particular, network size has no significant effect on E-Learning experience and knowledge value, since they are almost independent of network size.

Second, when studying relationship between network size and knowledge acquisition via E-Learning community, we realize that network size has limited effects on most key factors of knowledge acquisition. Often, new relationships between key factors of knowledge acquisition and network size emerge, and old ones disappear.

Although an efficient SNS oriented E-Learning community can bring more benefits for knowledge acquisition aspects in an organization, research in this field has remained sparse. Moreover, most previous literature focuses on micro-level knowledge flow while neglecting the features of macro-dynamics in the network organization.

Thus, considering an SNS oriented knowledge community with many members to acquire knowledge via E-Learning; we studied the macro effects of network size on key factors of knowledge acquisition caused by interaction of individuals in micro level. Compared with the existing approaches and results in previous literature, which mostly use questionnaires to test whether there are significant correlations between the knowledge flow and network size, our research develops computational models to conduct a virtual experiment; therefore, our results can help organization better understand the knowledge acquisition behavioral patterns of network organization in a general way.

The models we proposed can be used in E-Learning community, when we devise knowledge acquisition strategies, take actions and measure performance in managerial objectives. Consequently, E-Learning dominance can be achieved more speedily and consistently maintained in this way.

There are several interesting directions for future research. Firstly, with the effect of network size, analyzing key factors of knowledge acquisition is supposed to be useful in predicting E-Learning behaviors. However, such network size induced effect is platform specific; we need to discern different E-Learning platforms have unequal reactions to the same network size. Secondly, in the virtual experiment, though experiment results showed that key factors of knowledge acquisition change with network size over time and stick to a specific tendency, we did not provide a clear guidance on how to adjust the network size, which could be a key problem in future research for real-time SNS oriented knowledge community. Moreover, in this paper, we analyzed effects of the network size by computational models; however, other network structural characteristics should be included to explain general effects of network features on E-Learning behavior.

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