Simulation Model of Knowledge Complexity in New Knowledge Transfer Performance

Research-in-Progress

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ABSTRACT

Given the importance of knowledge transfer in individual performances, we assess the effect of knowledge flows complexity on knowledge transfer performance in a simulation model. In this regard this paper seeks to contribute to knowledge literature by proposing a new knowledge complexity framework, in which we explore the structural (diversity of knowledge type and depth of knowledge) and dynamic (loss of knowledge, knowledge creation pace) dimensions of knowledge flow complexity. Using an exploratory simulation study we propose the four aspects of knowledge flow complexity and test its effects on learners' occupation and learning system queues. As a research-in-process, our preliminary results support that knowledge creation pace with both dependent variables (busy time proportion of the learner and queue length of knowledge processing) is the strongest among all the relationships in sensitivity analysis comparison. The least change exists in the relationship from the percentage of knowledge loss to the dependent variables.

Keywords

Knowledge sharing, knowledge complexity, structural and dynamic complexities, simulation.

INTRODUCTION

In classic knowledge management literature (Alavi and Leidner 2001; Nonaka 1994), knowledge management has been recognized as identifying, integrating, and sharing company's knowledge, either tacit or explicit, so that constituents can use the knowledge resource to accomplish organizational goals (Morgan et al. 2003). Given the importance of knowledge, many studies have examined various aspects in knowledge management as a critical f-actor for -individual and firm performance, especially important for IT project performance (Bock et al. 2005; Nissen 2005-6; Ryu et al. 2005). It has been studied that organizational learning, especially knowledge transfer, has been affected by knowledge flow embedded in transmission technologies over a period of time (Epple et al. 1991). Knowledge transfer process is, however, complicated and dynamic (Nonaka 1994) making the activities including learning and absorbing knowledge unpredictable and uncertain. Many factors preorders knowledge transfer, for example, the team characteristics such as cultural and functional diversities of the team members, environment characteristics such as the communicating media richness, as well as knowledge characteristics such as the complexity of task. Although there are many studies in knowledge management that have examined knowledge transfer behaviors (Boland et al. 2001; Carlile 2004; Ko et al. 2005), sparse attention has been paid to provide a comprehensive knowledge attribute framework, such as complexity, and its influence on the knowledge sharing process. Moreover, the current approaches to knowledge transfer do not pay as much attention to the dynamic aspects as they pay to the static aspect of the knowledge flow.

From a methodological perspective, simulation has been a traditional research method in areas such as Operational Research or Management Science. In contrast, knowledge management area which is one of the latest change management topic is typically investigated by empirical approaches (e.g., (Nissen 2005-6)) or analytical methods (e.g.,(Ryu et al. 2005), and very little attention is paid to using simulation approach in this area of research (Harrison et al. 2007).

To fill these gaps, our research undertakes an investigation of knowledge complexity dimensions and their effect on the knowledge learning process. This study seeks to contribute to both the academic and the managerial audience in three ways. First, we develop a new framework for knowledge complexity composed of both structural and dynamic aspects of knowledge flow. Second, we develop a model that relates the new knowledge complexity of knowledge flow to the learning process. The model is designed to test the validity of the new framework and also contribute to the organizational learning literature. Third, we contribute to the knowledge management literature by testing our model with a simulation methodology to test the knowledge complexity items' effect on learning performance.

The rest of the paper is organized as follows. We review prior research in the knowledge complexity and the simulation methodology. We then propose a simulation model by assigning complexity item into modeling index with sensitivity analysis. We summarize the preliminary results and provide directions for future research.

LITERATURE REVIEW

Knowledge Complexity Framework Development

Knowledge has been described as a justified true belief that increases an entity's capacity for effective action (Alavi and Leidner 2001; Nonaka 1994). Knowledge Transfer is the process through which one individual is affected by the experience or knowledge of another (Argote et al. 2000). Considering the attributes of knowledge itself, knowledge transfer is not considered as complete unless a knowledge reservoir is moved from a sender to receiver or the reservoir itself is modified by the receiver (Argote et al. 2000). As Xia and Lee (2005) argue, in IT projects especially software development, task complexity is subjected to varied internal and external changes over time. They envision these complexities composed of two distinct aspects: structural and dynamic. Since the task in knowledge transfer is to handle knowledge, we apply the same complexity spirit as the knowledge attributes. Based on the literature in task complexity and knowledge transfer, the new framework is summarized in Table 1.

	Description	Items
Structural Complexity	variety and interaction, coordination and integration of knowledge elements	Diversity of knowledge type
		Depth of knowledge
Dynamic Complexity	uncertainty, variability, and dynamism, which is caused by changes in learning environments	Knowledge creation pace
		Knowledge obsolescence

Table 1. Knowledge Complexity Framework

Structural complexity is understood as variety, multiplicity, and differentiation of knowledge (Xia et al. 2005). Structural knowledge complexity can be described as "the degree of depth and specialization of the internalized knowledge of human experts" (Meyer and Curley 1991), and it requires both advance degree as PhD and a long-time working experience. When deep knowledge is transferred, learning requires more time and energy to apply more training and experience (Ryu et al. 2005). More deep the knowledge, more time-consuming is the learning process. Learning is also affected by the diversity of knowledge. When different types of knowledge comes in continuous sequence, learning process is expected to have different cognition setting modes increasing the setup time thereby increasing the learning process time.

Dynamic complexity is "uncertainty, ambiguity, variability, and dynamism, which is caused by changes in organizational and technological project environments" (Xia and Lee 2005). In our research, knowledge dynamic complexity is understood as knowledge update and obsolescence, which is caused by changes in learning environments such as changes in new technology development (Agarwal and Prasad. 1999). Dynamic knowledge complexity is relevant to and critical for knowledge transfer and absorption because knowledge developments on new media, such as popularity of iPhone4, are changing with extraordinary speed. In this paper we consider pace of creating new knowledge as the first dimension of dynamic complexity. The second dimension is related to the uncertainty of knowledge transfer: knowledge obsolescence, also referred to as deskilling (Cha et al. 2008). Thus we view that dynamic knowledge complexity may be influenced by uncertainty that may be a result of knowledge loss due to multiple team member miscommunications and the pace of new knowledge is creation. Knowledge is dynamically more complicated to transfer and share (Olivera et al. 2008), when new knowledge is more prone to lose during learning process or when the knowledge update is too frequent to be effectively received and processed by the receivers.

Knowledge Complexity and Learning

Main objective of knowledge management is to create, transfer and store knowledge (Nonaka 1994). Knowledge has many of attributes that influence group communication (Bock et al. 2005; Grant 1996). In this regard knowledge management has few things in common to supply chain management. In supply chain, the goods during the transfer influence the efficiency and effectiveness of system performance (Kärkkäinen 2003). Many factors such as team structures, media, and inherent knowledge characteristics shape knowledge transfer process. Since knowledge complexity reviews underlying knowledge domains and degree of knowledge complexity in decision-making process (Meyer and Curley 1991), it also reflects the efforts and difficulty in knowledge transfer process, which can be reflected as a supply chain difficulty. A study in supply chain management which developed a special purpose simulation tool, SCSIM, for analyzing supply chain (SC) behavior and performance especially in the environment in the presence of uncertainty (Petrovic 2001) gives a backdrop for this study.

Evidence suggests that effective knowledge transfer of diverse knowledge forms and sources is a critical activity that ensures the success of knowledge integration involving high level of interaction and social presence to learn (Dennis et al. 2008; Sarker et al. 2005). Knowledge depth is one index for domain specific level. Therefore, the inter-correlation among such knowledge is high based on its definition (Meyer and Curley 1991). To master such knowledge, receivers need rebuild the exiting knowledge network and reframe certain clarification as learning process. Therefore, higher the level of knowledge diversity and depth, more complicated is the knowledge learning process. Frequent knowledge can be easily represented as knowledge update with high pace or high level of knowledge loss during transfer processes. More frequent is the knowledge replacement, more works is need for the receiver to change during limited working period. Information overload occurred with personal confusion, working conflicts and so on. Such negative influence is part of negative results of learning curve phenomena (Epple et al. 1991).

Simulation Methodology

In historical scientific methodologies, there are mainly two types: theoretical analysis (deduction) and empirical analysis (induction). Computer simulation is recognized as a third type of scientific research method. Simulations resemble deduction in that the outcomes from the assumptions made resemble induction inferred from analyzing the output data (Harrison et al. 2007). Simulation modeling is the development of a model of the system with computer program or software, which enables investigation of the system's performance subject to a variety of operating conditions or behaviors (Pidd 1998).

Simulation can be used to discover consequences of processes interaction. Frequently, behaviors are observed, but it is not clear what processes produce the behaviors. Specific underlying processes can be postulated and their consequences examined with a simulation; if the simulation outcomes fit well with the observed behaviors, then the postulated processes are shown to provide a plausible explanation for the behaviors. In operations research there is a vast amount of research using simulation in queuing situations (Demers et al. 1989). Efficient ways of workflow setting for change management in organizational procedures serve as a basis in these studies. In the ten-year period 1994 to 2003, 23.6% of *Management Science* publications involve simulation across various disciplines. Tons of research justifies software simulation in supply chain management, for example, *Decision Science* special issue of supply chain linkage in 1998 has proved simulation to be a useful tool (Mabert and Venkataramanan 1998). The outcomes of interest are often some function of the structure and behavior of the management system and need to be calculated from organization policies (Chen et al. 2000). Agent-based models mimic the behaviors of adaptive actors who make up a social system and who influence one another through their interactions. Outcomes may be calculated for each time period or only at the end of the run in each simulation, depending on the simulation's purpose (Harrison et al. 2007). These tools are not a core part of a simulation model but are becoming critical to the usefulness of the model in business or specifically IT applications (Harrison et al. 2007).

Arena software is designed as a powerful tool to create animated simulation models representing virtually any system. It can be on a system layout with components such as machines, operators, and raw materials (Takus and Profozich 1997). Since knowledge management system is proposed as a transmission system, we also follow the logic in the above mentioned simulation studies and examinate the system where the knowledge complexities serve as inputs to the system. Each complexity dimension can be transferred into different indices in the learning model simulation. High level of diversity and depth indicates longer time to process such knowledge in simulation. Also, the creative pace is controlled by the creation time of knowledge release. To represent frequent knowledge transfer, the time window between knowledge flows is shortened. Finally for knowledge obsolescence, a percentage of loss is added into the transmission to account for the knowledge loss.

MODEL DEVELOPMENT

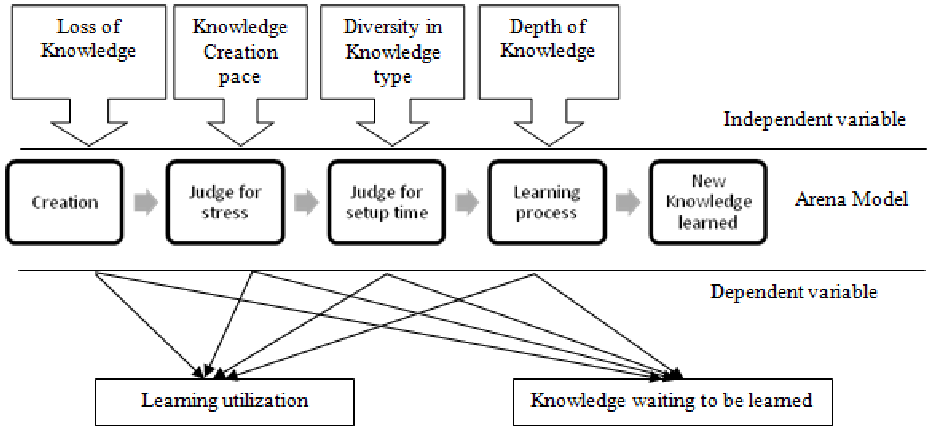

Figure 1. Research Model

Figure 1 captures the model examined in this study where the independent variables include structural complexity (diversity of knowledge type, knowledge depth) and dynamic complexity (knowledge loss, new knowledge creation pace). Each of these independent variables influences the stages of the first layer. The second layer is the simulation beginning with new knowledge flow creation. Actual knowledge creation time is compared to mean of the creation time, and when the knowledge comes quicker than average, the on-coming knowledge is viewed as waiting in lines to be processed. Waiting knowledge in learning queue generate pressure for learner to absorb the knowledge in process. The emotional pressure delays the normal learning performance, by the same proportion as the variance by the knowledge creation from the mean. Due to the different distribution of knowledge types, sequence of the knowledge type may be different or the same. When the same types of knowledge are created, there is no set up time. Otherwise, a positive setup time is required to prepare the following new knowledge processing. When learner finally faces the knowledge, depth of the knowledge decides the knowledge processing, such as combining stored knowledge, comprehending the meanings. Dependent variables in layer 3 of Figure 1 is learning utilization referring to percentage of time learners are busy learning new knowledge during the whole knowledge transfer, and waiting knowledge to be learned,,which is the knowledge in queue.

METHODOLOGY – SIMULATION

Figure 2 below presents a model in Arena Software. It begins with the knowledge creation, then tests for the stress status of the learner. Then the knowledge might be lost after a certain distraction during the process. Before the knowledge processing, a set-up time is also added up to the processing if current knowledge type is different from the previous one. The system keeps records of the learner utilization and knowledge waiting time.

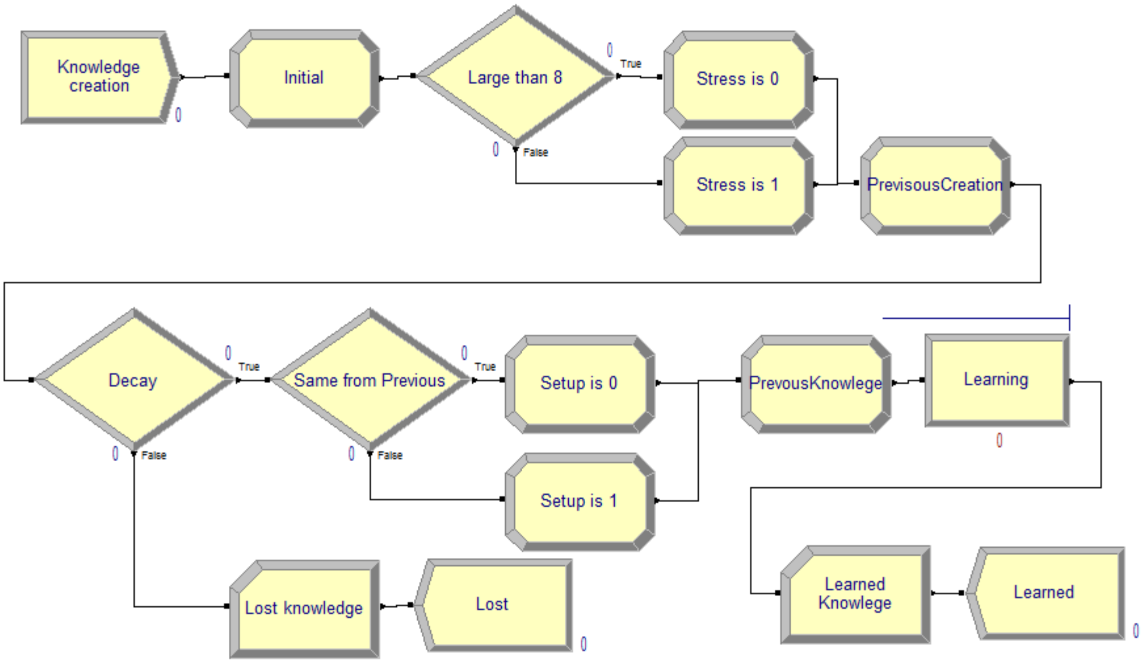

Figure 2. Arena Simulation Model

We assume that there are two types of knowledge being transferred. To change the diversity we look at the distribution of these two types of the knowledge. If the process consists each of the two types of knowledge being 50%, knowledge diversity turns up to be 1-0.5^2-0.5^2 = 0.5, which is the possible highest value. Depth and creation pace is assumed to follow normal distribution. The model baseline setting should also make sure that queuing length is larger than zero; therefore the process time should be a little larger than the creation pace to assure valid dependent variable measurements. In the basement setting, creation pace is Normal (8, 2.5) (average 8 hours with 2.5 hours of deviation for new knowledge creation) and process time is Expo Normal (2, 0.6) (average 2 hours with deviation of 0.6 hours for processing the new knowledge). We use the following setting to avoid the negative results within system capability limits. The choice of exponential processing time function is rooted in knowledge learning literature, and is widely used in management field (Yelle 1979). Finally is the knowledge loss during transfer, is defined as uniform rate of 3-5% (Ryu et al. 2005). Considering a typical project/project-milestone of 3-4 months with 8-hour workday, each simulation is set up for 500 hours with 100 replications. All the tables use hours as measurement index. For each indicator, we summarize the original setting in Table 2.

	Items	Simulation Setting
Structural Complexity	Diversity of knowledge type	Two type of knowledge: Uniform (0.5, 0.5) Setup time: Normal(1,0.1)
	Depth of knowledge	Process time for learning: expo(normal(2,0.6))
Dynamic Complexity	Knowledge creation pace	Creation time distribution: normal(8,2.5)
	Knowledge obsolescence	Percent of knowledge loss: [100-Uniform(3,5)]%

Table 2. Knowledge Complexity in Simulation

RESULTS AND DISCUSSION

Sensitivity Analysis

The sensitivity analysis changes one independent variable at a time to see the changes of dependent variables. Therefore, we can compare each independent variable's influence on both dependent variables. Also each change is to add or subtract 10% of the original value. For the diversity sensitivity analysis, we consider another scenario with 40% of one type and 60% of other type of knowledge, where diversity is 1-0.4^2-0.6^2 = 0.48. Each independent variable changes the mean and standard deviation. In each table 2, "average" is the mean of 100 replications of the simulation, "min average" is the smallest result in all the 100 implications. Similarly, "max average" is the largest mean of one simulation among all the 100 implications. The sensitivity numerical results are displayed in Appendix Table 3(a-e).

The sensitivity analysis results are also presented in graph of Figure 3 and Figure 4. Figure 3 indicates that mean of changing pace is the strongest factor that influences the learner utility (% of knowledge absorption time) from 36.06% to 87.64% and waiting knowledge to be learned from 0.0451 hours to 2.49 hours (Table 3.a). Since the setting of such pace is an approximate estimate based on balance of arrival and service rate in queuing theory, the pace dominates the position of stronger influence than the mean of depth. The percent of loss, not surprisingly, represents the least effective factor to both dependent variables.

Both learner utilization and waiting knowledge increase with creation rate, knowledge depth, knowledge type diversity and setup time, meanwhile decrease with percentage of loss. The range of the changes differs between the two. With the same change in knowledge creation pace, waiting knowledge became 60 times larger than original setting and learner utilization increased by close to 2.5 times (Figure 3 and Figure 4).

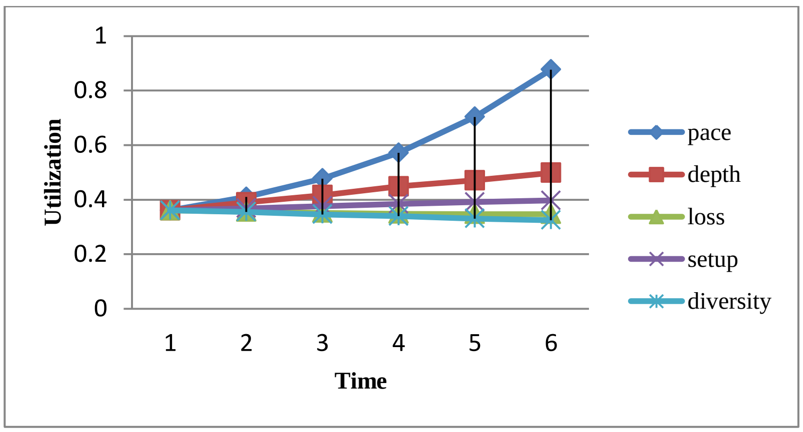

Figure 3. Summary of Learner Utilization

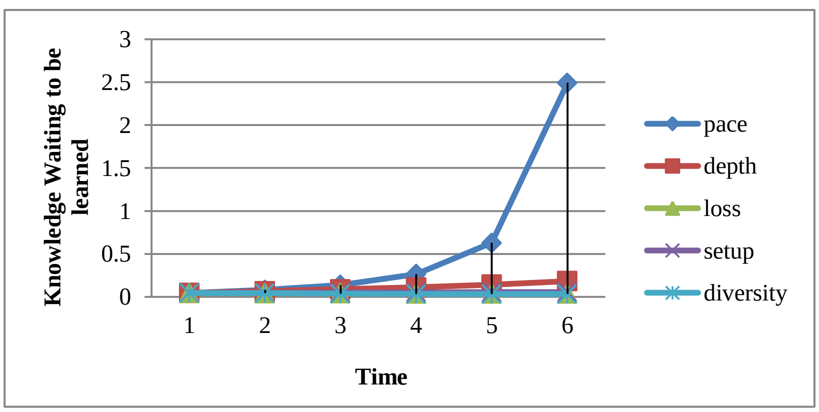

Figure 4. Summary of knowledge waiting to be learned

Results Discussion

We hope to make two significant contributions to the knowledge transfer literature with this study. First, we hope to contribute by proposing a new comprehensive framework of knowledge complexity based on an in-depth qualitative knowledge literature review. The second, the specific relationships between the four complexity dimensions and learning performance is tested in an ARENA simulation model with a sensitivity analysis. Preliminary results of 100 replications show evidence of the two contributions that we hope to make through our final study. Our preliminary results also provide some insights that we discuss in the following paragraphs.

The relationship of knowledge creation pace with both dependent variables (busy time proportion of the learner and queue length of knowledge processing) is the strongest among all the relationships in terms of sensitivity analysis comparison. This suggests that knowledge inflow pace is one of the most important knowledge complexity dimensions when it comes to occupying the learning time and workloads. This should come as no surprise because frequency of knowledge sharing or transfer is one of the most studied input indexes in the supply chain literature due to its central and important role in queuing theory.

The least change exists in the relationship from the percentage of knowledge loss to the dependent variables. This is a typical simulation result. Since knowledge loss is the most intuitive predictor in knowledge sharing without any other moderation effects, the initial percentage is set as the same as one in an existing MISQ publication (Ryu et al. 2005). Our simulation results support that among all those factors, knowledge loss is the least important and sensitive factor to both learner utilization and knowledge waiting to be learned. Although diversity of knowledge significantly yields the learning performances, the evenly-distributed two domains of knowledge flows serve the best predictors among the two possible types of knowledge flow in combination.

CONCLUSION AND FUTURE RESEARCH

In this research, we examine the impact of knowledge flow complexity on knowledge transfer performance. This paper develops a knowledge complexity framework, in that we explore the structural and dynamic dimensions of knowledge flow complexity. Similar to task complexity dimensions, knowledge complexity can also be understood as structural and dynamic complexity. Internal structural complexity is inherent to knowledge itself resulting from variance in knowledge styles. If more different types of knowledge are transferred, additional information and processing may be necessary to change cognitive modes for new knowledge learning. Another item of structural complexity is the depth of knowledge, where academic education focuses on learning requirements for a learner to absorb and finally master the knowledge. When structural knowledge pictures the internal framework, knowledge dynamic complexity captures the complexity from time dimension. Changing rate of knowledge and uncertainty encapsulate the idea of knowledge management processes over time. Creation of new knowledge pace is different according to changing environments or technology and uncertainty of complexity.

Learning behaviors is hard to observe because learning happens inherently within individuals,, which is hard to quantify and measure. Specific underlying processes can be postulated and their consequences examined with a simulation, then the postulated processes can be shown to provide a plausible explanation or improvement for the behavior results. A simulation of learning shows that the knowledge adoption takes time and energy in the face of change in knowledge transfer. The exploratory use of simulations is related to the use of simulation as existence proof and highlights the conditions under which such outcomes are produced. Using an exploratory simulation study we test four aspects of knowledge flow complexity – loss of knowledge, knowledge creation pace, diversity in knowledge type and depth of knowledge – to gain a better understanding of the effect of the complexity aspects on knowledge transfer performance. This is the first comprehensive study that looks at both structural and dynamic aspects of knowledge flow complexity. To develop this research in progress paper further, we would validate our framework using real data and by suggesting implications to theory and practice.

There are several limitations in our current research. First, we only consider the simplest scenario, only changing one independent variable at one time in sensitivity analysis. In actual world, one, the introduction of new technology in project management not only requires depth and but also enhances the new knowledge creation pace. Second, simulation as a research method also has its limitation, such as potential problems that arises from the translation of the formal model into computer code (Harrison et al. 2007). For example, the order in which more than many processes are carried out in the same model during a given time period may differ the results. We also hope to address these in our future research. Furthermore, other quantitative research methods can be also used to support our research argument. Detailed survey method will provide more realistic reflections of the concept and SEM can serve as an appropriate tool to support the hypothesized relationship between knowledge complexity dimensions to learning performance.

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APPENDIX

Knowledge creation pace	Learning Utilization (% of knowledge absorption time)			Knowledge contents waiting to learned		
	Average	Min average	Max average	Average	Min average	Max average
normal(8,2.5)	0.3606	0.2457	0.4642	0.0451	0.00016	0.1646
normal(7.2,2.25)	0.4099	0.2807	0.5836	0.0815	0.00907	0.4235
normal(6.4,2)	0.4768	0.3397	0.6893	0.1392	0.0249	0.9357
normal(5.6,1.75)	0.5713	0.4108	0.745	0.2658	0.043	1.4089
normal (4.8,1.5)	0.703	0.5456	0.8667	0.628	0.1105	2.6051
normal (4,1.25)	0.8764	0.6723	1	2.4907	0.5171	14.8315

Table 3a. Sensitivity Analysis Results: knowledge creation pace

Depth of knowledge	Learning Utilization (% of knowledge absorption time)			Knowledge contents waiting to be learned		
	Average	Min average	Max average	Average	Min average	Max average
normal(2,0.6)	0.3606	0.2457	0.4642	0.0451	0.00016	0.1646
normal(2.2,0.66)	0.39	0.2637	0.5012	0.0664	0.00398	0.2238
normal(2.4,0.72)	0.4159	0.2818	0.5838	0.08936	0.011948	0.5086
normal(2.6,0.78)	0.4482	0.2998	0.5615	0.1104	0.01829	0.4925
normal (2.8,0.84)	0.4709	0.3178	0.6514	0.1434	0.023987	0.7051
normal (3,0.9)	0.4982	0.3358	0.7091	0.1834	0.033948	0.7173

Table 3b. Sensitivity Analysis Results: depth of knowledge

Knowledge loss	Learning Utilization (% of knowledge	Knowledge contents waiting to be learned

	absorption time)					
	Average	**Min average**	**Max average**	**Average**	**Min average**	**Max average**
uni(3,5)	0.3606	0.2457	0.4642	0.0451	0.00016	0.1646
uni(3.3,5.5)	0.3556	0.2457	0.501	0.04387	0.000169	0.1646
uni(3.6, 6)	0.3518	0.2239	0.501	0.0432	0	0.1646
uni(3.9,6.5)	0.3479	0.2239	0.501	0.04077	0	0.1646
uni(4.2, 7)	0.3469	0.2457	0.4657	0.0404	0.000169	0.1289
uni(4.5,7.5)	0.3469	0.2457	0.4657	0.04085	0.000169	0.1289

Table 3c. Sensitivity Analysis Results: knowledge loss

Knowledge creation proportion	**Learning Utilization (% of knowledge absorption time)**			**Knowledge contents waiting to be learned**		
	Average	**Min average**	**Max average**	**Average**	**Min average**	**Max average**
0.5, 0.5	0.3606	0.2457	0.4642	0.0451	0.00016	0.1646
0.45, 0.55	0.355	0.2453	0.4831	0.04414	0	0.1362
0.4, 0.6	0.3456	0.2369	0.4969	0.03669	0	0.1296
0.35, 0.65	0.3392	0.2423	0.4694	0.0327	0	0.1734
0.3, 0.7	0.3305	0.233	0.457	0.032	0	0.1883
0.25, 0.75	0.3248	0.2119	0.4304	0.0326	0	0.2017

Table 3d. Sensitivity Analysis Results: knowledge type

Setup time	**Learning Utilization (% of knowledge absorption time)**			**Knowledge contents waiting to be learned**		
	Average	**Min average**	**Max average**	**Average**	**Min average**	**Max average**
normal(1,0.1)	0.3606	0.2457	0.4642	0.0451	0.00016	0.1646
normal(1.1,0.11)	0.3681	0.2523	0.4726	0.04712	0.000169	0.168
normal(1.2,0.12)	0.3761	0.2588	0.481	0.05077	0.000226	0.189
normal(1.3,0.13)	0.3841	0.2654	0.4893	0.05357	0.000494	0.1987
normal(1.4,0.14)	0.3907	0.2719	0.4977	0.05575	0.00083	0.2038
normal(1.5,0.15)	0.397	0.2785	0.5061	0.057726	0.00127	0.2131

Table 3e. Sensitivity Analysis Results: setup time