Individual Learning Pattern Related to Intention
with a Biological Model of Knowledge Construction

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Abstract: In an e-learning system, it is difficult to grasp the learner's condition for learning. In the face-to-face learning environment, we tend to notice if there is something unusual about learners and help them out of difficulties. In addition, we often cannot keep learners from dropping out of the e-learning course. This suggests a requirement for a research study specially focused on how to predict the learner's condition with the learning log data in the e-learning system. Therefore, we drew up a learning model with biological knowledge from the latest molecular biology and brain science. In this paper, results from our learning model were verified by comparison with real learning log data in an e-learning system. Our model suggests that there is a learning type with high intention who prefers to learn in a short term in order to construct his/her knowledge. Then we examined the data related to intention, and it correlated closely with the learning period of one exercise.

Keywords: Knowledge construction, learning pattern, biological model, dopamine.

1. INTRODUCTION

Originally, humans are by nature animals capable of learning in social life. The primordial form of learning is "learning by doing." However, the concept of literacy appeared, thus leading to the production of modern schools at which students participated in unique learning forms. That is, schools were originally used as a "virtual" space for learning. Gradually, school life became an important part of social life. Knowledge acquired in school has been thought of as a ticket to success, but as it is a space for learning, unfortunately various contradictions to the school form have been showing up with the development of information technology. This is due to information technology having the capacity to allow humans to have real and up-to-date knowledge.

Taking into account the historical background, the potential of the e-learning system for natural human learning should be studied. The ability to learn anytime and anywhere has been improved by information technology and researchers begin to discuss the learning theory with constructivism in a new educational way by e-learning. For example, as an environment for situated learning, Grabinger and Dunlop (1995) constructed "Rich Environment for Active Learning (REALs)," and Nunes and McPherson (2002) built "Continuing Professional Development Education (CPDE)" as a new continuous vocational education.

Developing those concepts, the learning grid is a current topic. For instance, the European Learning GRID Infrastructure (ELeGI) project background of learning theory by Vygotsky, Lave and Wenger (ELeGI, 2005). In the ELeGI project, a new learning environment must be discussed. This is the most important topic in making a new learning model. Looking back on the primordial form of learning, a desire of learning comes naturally and humans can learn by themselves with information technology according to the concept of the learning grid.

Here, we would like to think about human desire for learning as coming from nature. We are able to feel the learner's enthusiasm in the face-to-face learning environment of, for example a classroom in school, and thereby support them in an appropriate manner to construct their knowledge. On the other hand, it is difficult to grasp the learner's condition in an e-learning system. Next, we focused on how to predict the learner's condition with the learning log data in an e-learning system.

First, we generated a biological model of knowledge constructions with three factors: emotion, memory and intention (Ninomiya et al. 2005). Each factor simulates chemical reactions which are thought to relate strongly to the latest models in molecular biology and brain science. The results from simulating the learning model suggest that there is a typical learning pattern in those with a high intention personality. In addition, a person of this type is likely to prefer to learn in the short term in order to construct his/her knowledge effectively.

Next, an e-learning course, where learners could access anytime and anywhere, was put into practice. Learners could work out their own plan and carry it out as they like. Although exercises and tasks were given at regular intervals, the deadline of all the assignments was three months and a day. From the learner's viewpoint, the freedom of learning is guaranteed and learners could deal with the exercises and tasks whenever they want. This model suits our aims to get learning log data that originates from the natural desire of learning.

Finally, we examined the learning log data in an e-learning course. In our biological model, the learning pattern suggested that a person with high intention starts constructing knowledge. By contrast, a learner with middle intention starts constructing knowledge after three instructional stimuli. Then, we supposed that the high intention person accesses less than two times for one exercise or task, and that the number of accesses to each exercise or task is one index for the strength of a learner's intention. As well as this typical learning pattern, a person with high intention prefers to learn within a short period of time in the biological model. Therefore, as other indices we chose the number of days between first and final access to one exercise or task and the number of days from task-done to deadline, and it was found that the number of accesses is correlated closely with the number of days from task-done to deadline. Considering these results, there is some possibility of predicting the learner's condition with our biological learning model, and we can provide learners with a suitable learning environment by predicting their learner's condition in the future.

2. BIOLOGICAL LEARNING MODEL

2.1 Biological factor and simulation model

Our model of knowledge construction incorporates both the biological mechanisms of the human brain and the environment to which a learner is exposed in the growing and learning period. First, a few important biological mechanisms related to cognition were selected from knowledge gained in pioneering studies. Furthermore, as there is no doubt about the influence of gene–environment interactions in human development (Botto and Knoury 2001), the influence of environment, including education, was integrated into the model.

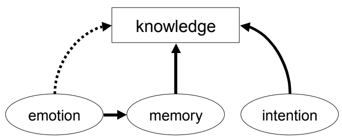


Figure 1. Knowledge model with three factors

We chose three factors: memory, emotion and intention, as there have been sufficiently large numbers of medical case reports (Damasio 1994, 1999) and imaging studies (Bush 2000) to indicate that complicated interactions between these factors affect human cognition. Thus, under the assumption that cognition is influenced by memory, emotion and intention, we made a model of knowledge construction as shown in Figure 1.

To simulate human cognition-related metabolism, several chemical substances that affect emotion, memory, and intention were chosen as shown in Table 1 (Milner 1998, Bliss 1993, Kandel 2001, Poo 2001, Egan 2003, Tang 1999, Dubnau 2003, Gross 2002, Murphy 2001, Gainetdinov 1999, Hariri 2002, Swanson 1998, LaHoste 1996).

Table 1. Chemical substances related to three factors

Factor	Definition	Chemicals
emotion	moods or feelings such as delight, anger, sadness and happiness	serotonin
memory	brain networks that support episodic memory, logical mind, *etc.*	BDNF, NMDA
intention	motives such as wish and desire	dopamine

Figure 2 shows the addition of metabolism to the three-factor knowledge model shown in Figure 1. In Figure 2, ellipses indicate genes and metabolic events such as secretion and absorption of chemical factors are indicted by hexagons. The volume of knowledge, memory, and chemical substances, such as serotonin and dopamine, are shown as rectangles.

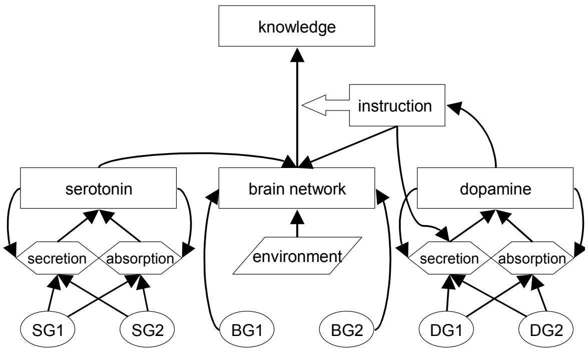


Figure 2. Metabolism model of knowledge construction

Early observations regarding differences in learning ability that emerge from enriched and restricted environments indicated that there are genotype-environment interactions (Cooper 1958). Therefore, the environment control device is set up in brain networks, in addition to those for genes.

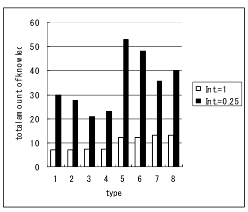
2.2 Results of simulation model

In our biological model of knowledge construction, the relation between learning pattern and dopamine metabolic rate is shown in Table 2. Other factors, such as serotonin, brain network, environment, and instruction, have no effect on these learning patterns.

Table 2. Learning pattern and dopamine metabolic rate

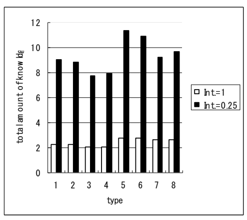
Dopamine metabolic rate	Learning pattern
Low (on=0, off=2)	get NOTHING from instructions (knowledge=0)
Intermediate (on=1, off=1)	get knowledge from THIRD instruction
High (on=2, off=0)	get knowledge from BEGINNING of instruction

Figure 3a. Final amount of knowledge (with enriched environment)



type	(M,E,I)
1	(1,1,2)
2	(1,2,2)
3	(1,1,1)
4	(1,2,1)
5	(2,1,2)
6	(2,2,2)
7	(2,1,1)
8	(2,2,1)

Figure 3b. Final amount of knowledge (with restricted environment)



type	(M,E,I)
1	(1,1,2)
2	(1,2,2)
3	(1,1,1)
4	(1,2,1)
5	(2,1,2)
6	(2,2,2)
7	(2,1,1)
8	(2,2,1)

When the interval of instructional stimuli is four times as much as Int.=1, several types benefit from intensive courses. These results are shown in Figure 3a,b.

In particular, types 5 and 6 benefit a great deal from intensive instructional stimuli. These types have a high dopamine metabolic rate as well as an elevated rate of building brain networks. In those with an intermediate metabolic brain network rate, the types with high dopamine metabolic rates also show an increased final amount of knowledge.

3. PRACTICE IN AN E-LEARNING COURSE

An e-learning course of duration three months was put into practice and learners could access the course anytime and anywhere. The outline is shown in Table 3. Thirty-six persons took this course to earn credits for graduation of a postgraduate course. Before starting the course, an orientation and a lecture were given. The learners were allowed to make their own learning plan and to carry out the exercises and tasks as they liked. Although exercises and tasks were given once a week constantly, all deadlines were set a day after three months. This meant that learners had the opportunity to plan their learning schedule and their way of study freely.

Table 3. Outline of the e-learning course

	content
period	2005/05/02-2005/08/09
subject	Artificial Intelligence and Knowledge Management
Topic	9 sub-subjects
exercise	27 tests
Task	9 reports
learner	36 persons (undergraduates, postgraduates and working members of society)

In our biological model, a person with a high dopamine metabolic rate starts constructing knowledge at once. By contrast, a person with a middle dopamine metabolic rate starts constructing knowledge after three instructional stimuli. Moreover, we supposed that a high dopamine metabolic rate person accesses less than two times per exercise or task, and the number of accesses to each exercise or task is construed to be one index of the strength of a learner's intention. The index is expressed by the term "access." As a person with a high dopamine metabolic rate prefers to learn within a short-term in the biological model, the number of days between first and final access with one exercise or task was chosen as the second index. This index is expressed by "period". As well as these two indices, two other indices were examined: the number of days between presenting the tasks and first access and the number of days between final access and deadline. These indices are expressed by "start" and "finish", respectively.

First, we examined the learning log data in the above course between exercises and tasks. Exercises such as short tests were easier than tasks in which learners had to investigate some papers or write a program for a computer. As they were different kind of tasks, it was necessary to check the correlations between these tasks in each index (Table 4). The means of each index for a person was used for calculations.

Table 4. Correlations between different kinds of tasks

	access	period	start	finish
all – test	0.58	0.86	0.99	0.98
all - report	0.89	0.38	0.95	0.93
test - report	0.89	-0.12	0.89	0.86

The important indices “access” and “period” showed low correlations, so correlations between indices were examined for every kind of task (Table 5).

Table 5. Correlations between each index

	All			Test			Report		
	period	start	finish	period	Start	finish	period	start	finish
access	0.24	0.07	-0.41	-0.10	0.13	-0.12	0.61	-0.07	-0.47
period		0.46	-0.39		0.47	-0.33		-0.24	-0.48
start			-0.78			-0.80			-0.63

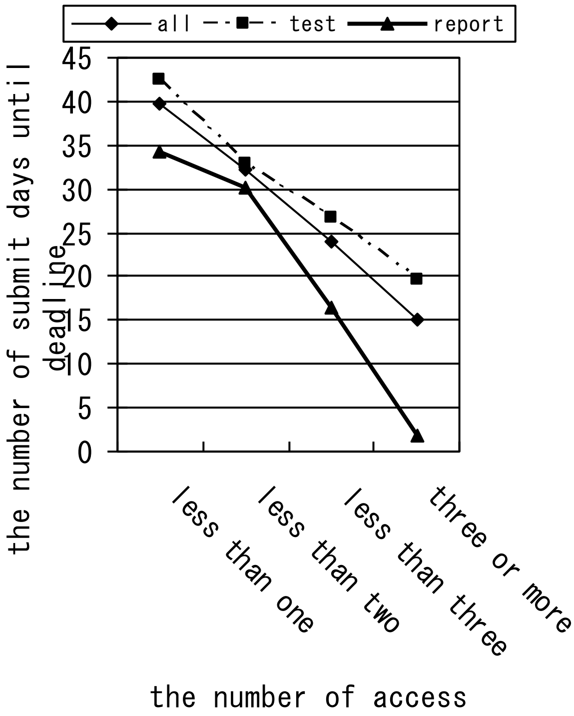
There are low correlations in Table 5 because the sample size is likely to be small for this investigation. Then the log data was divided into subgroups for each index. For the access index, learners were divided into four sub-groups: 1) less than one access, 2) less than two accesses, 3) less than three accesses and 4) three or more accesses. For the period index, learners were divided into four sub-groups: 1) less than four days, 2) less than eight days, 3) less than twelve days and 4) twelve or more days. For the start index, learners were divided into seven sub-groups: 1) within one week, 2) within two weeks, 3) within three weeks, 4) within four weeks, 5) within five weeks, 6) within six weeks and 7) after six or more weeks. For the finish index, learners were divided into eight sub-groups: 1) within two weeks, 2) within three weeks, 3) within four weeks, 4) within five weeks, 5) within six weeks, 6) within seven weeks, 7) within eight weeks and 8) before eight or more weeks. The correlations between the four indexes are shown in Table 6 after grouping sub-groups.

In Table 6, highest correlations are seen between the access index and the finish index. Therefore, we plotted the relation between these two indexes in Figure 4 below. Regardless of the number of days until the deadline, people with fewer accesses tend to finish their tasks as soon as possible. That is, it is likely that a person with high dopamine metabolic rate prefers to learn within a short term. As even the person with high dopamine metabolic rate accesses more than one with reports, the correlation of report between access and period is the highest as well.

Table 6. Correlations between each index after grouping

	access		
	period	start	finish
all	0.77	0.69	-0.99
test	0.55	0.99	-0.92
report	0.99	-0.25	-0.98
	period		
	access	start	finish
all	0.95	0.51	-0.99
test	0.97	0.87	-0.96
report	0.31	-0.68	-0.82
	start		
	access	period	finish
all	-0.01	0.79	-0.88
test	-0.05	0.76	-0.90
report	-0.15	-0.48	-0.78
	finish		
	access	period	start
all	-0.90	-0.86	-0.85
test	-0.20	-0.67	-0.85
report	-0.88	-0.71	-0.78

Figure 4. Relation between "access" and "finish"



With these results, it was concluded that the number of accesses is correlated closely with the number of days from task-done to deadline. Therefore, there is some possibility of predicting the learner's condition with our biological learning model, and we can provide learners with a suitable learning environment by predicting the learner's condition in future.

4. CONCLUTION

The results of simulations in the biological and social model of knowledge construction suggested that a certain inborn biological function must determine the personal learning pattern, regardless of other functions and environmental influences. Furthermore, intensive training was shown to be effective in high dopamine metabolic rate types of learning. With these simulation results, we examined the data related to intention. It was found that the number of accesses is correlated closely with the number of days from task-done to deadline. Thus, there is a possibility of predicting the learner's condition with our biological learning model.

5. REFERENCES

Bliss, T.V. and Collingridge, G.L., 1993. A synaptic model of memory: long-term potentiation in the hippocampus. *Nature,* Vol.361, pp.31–39.

Botto, L.D. and Khoury, M.J., 2001. Facing the challenge of the gene-environment interaction: The two by for table and beyond. *American Journal of Epidemiology*, Vol.157, pp.1011–1020.

Bush, G. *et al*., 2000. Cognitive and emotional influences in the anterior cingulated cortex. *Trends in Cognitive Sciences*, Vol.4, pp.215–222.

Cooper, R.M. and Zubek, J.P., 1958. Effects of enriched and restricted early environments on the learning ability of bright and dull rats. *Canadian Journal of Psychology*, Vol.12, pp.159–164.

Damasio, A.R., 1994. *Descartes' Error: Emotion, Reason and the Human Brain.* Putnam Pub Group Published, NY, USA.

Damasio, A.R., 1999. *The Feeling of What Happens: Body and Emotion in the Making of Consciousness.* Harcourt Published, CA, USA.

Dubnau, J., *et al*., 2003. The staufen/pumilio pathway is involved in Drosophila long-term memory. *Current Biology*, Vol.13, pp.286–296.

Eagan, M.F., *et al*., 2003. The BDNF val66met polymorphism affects activity-dependent secretion of BDNF and human memory and hippocampal function. *Cell*, Vol.112, pp.257–269.

ELeGI org., 2005/7. GRID Technology for Learning: the "European Learning GRID Infrastructure" project. http://www.elegi.org/.

Gainetdinov, R.R., *et al.* 1999. Role of serotonin in the paradoxical calming effect of psychostimulants on hyperactivity. *Science*, Vol.283. pp.397–402.

Grabinger, S. and Dunlop, J. 1995. Rich environments for active learning. *Association for Learning Technology Journal*, 3(2), pp5-34.

Gross, C., *et al*., 2002. Serotonin 1A receptor acts during development to establish normal anxiety-like behavior in the adult. *Nature*, Vol.416, pp.396–400.

Kandel, E.R., 2001. The molecular biology or memory storage: a dialogue between genes and synapses. *Science,* Vol.294, pp.1030-1038.

Hariri, A.R., *et al.*, 2002. Serotonin transporter genetic variation and the response of the human amygdala. *Science*, Vol.297, pp.400–403.

LaHoste, G.J. *et al*., 1996. Dopamine D4 receptor gene polymorphism is associated with attention deficit hyperactivity disorder. *Molecular Psychiatry,* Vol.1, pp.121–124.

Milner, B. *et al*., 1998. Cognitive neuroscience and the study of memory. *Neuron*, Vol.20, pp.445–468.

Murphy, D.L., *et al*., 2001. Genetic perspectives on the serotonin transporter. *Brain Research Bulletin,* Vol.56, pp.487–494.

Ninomiya, T. *et al*., 2005. Social and biological model of cognitive development and learning pattern. *CELDA 2005,* pp.18-25.

Nunes, J.M. and McPherson, M.A. 2002. Pedagogical and implementation models for e-learning continuing professional distance education (CPDE) emerging from action research. *International Journal of Management Education*, 2(3), pp16-25.

Poo, M.M., 2001. Neurotrophins as synaptic modulators. *Nature Reviews Neuroscience,* Vol.2, pp.24–32.

Swanson, J. *et al*., 1998. Cognitive neuroscience of attention deficit hyperactivity disorder and hyperkinetic disorder. *Current Opinion in Neurobiology,* Vol.8, pp.263–271.

Tang, Y.P.,. *et al*., 1999. Genetic enhancement of learning and memory in mice. *Nature,* Vol.401, pp.63–69.