A STUDY ON THE COMPARATIVE ADVANTAGES OF CONCEPT MAP CONSTRUCTION AND SELF-EXPLANATION

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ABSTRACT

Being knowledgeable means not only knowing the concepts, ideas, terms, and rules that make up the knowledge domain, but also entails a correct understanding of their interrelationships. Concept maps have been found effective in representing those meaningful relationships and enhancing students' learning activities. In this research, we examine whether concept mapping can be further improved by incorporating self-explanation activities. Specifically, while controlling for total training time, we compared three alternative learning conditions: a control group (no concept mapping), a regular concept mapping group (provided with an expert skeleton diagram), and a concept mapping reinforced with self-explanation group (started with an expert skeleton and finished with self-explanation activities), in the experimental setting of learning a new programming language, Ruby. Sixty undergraduate and graduate students at KAIST (Korea Advanced Institute of Science & Technology) participated in the experiment. The results overall indicate that the proposed method of concept mapping reinforced with self-explanation is the most effective among the three experimental conditions and can further enhance the training efficacy of the concept mapping methodology.

Keywords: knowledge structure, concept map, self-explanation, assimilation theory, programming training, computer education, Ruby programming language

1. INTRODUCTION

Over the past two decades, the concept map has emerged as a resourceful and promising tool used in research aimed at investigating students' conceptual understanding, often referred to as cognitive structure (Acton, et al. 1994) or structural knowledge (Jonassen et al. 1993). The concept map, a graphical tool to organize and represent knowledge, has been found effective in representing meaningful relationships between concepts and improving students' learning performance in various domains, particularly the sciences. Although many studies have demonstrated the effectiveness of concept mapping as a learning method, we were concerned about a fundamental improvement of the current concept mapping technique. Consequently, we considered *self-explanation*, a well-attested learning theory. The process of self-explanation involves students forming inferences, beyond the provided information, and has been found to facilitate the learning process by supporting and extending existing knowledge.

A review of the literature revealed little research has been done on integrating the concept mapping process with self-explanation. There is one study of which we are aware that attempted to integrate concept mapping and self-explanation. Hilbert and Renkl (2009) conducted two experiments involving heuristic example-based learning in the acquisition of basic computer-based concept mapping skills. Against expectations, the first experiment did not reveal improvements in learning outcomes nor conceptual knowledge about concept mapping. The second experiment incorporated self-explanation prompts which resulted in marginal improvements over the control group. Given the low learning outcomes, we felt unanswered questions remained in terms of whether concept mapping could be improved by incorporating self-explanation techniques. To that end, the goal of this research is to address the following questions:

- Can concept mapping be integrated with self-explanation theory in a way that leads to appreciable improvements in learning outcomes?
- To what extent does the proposed concept mapping method improve declarative knowledge and skills?
- To what extent does the proposed concept mapping method improve procedural knowledge and skills?

We differentiate between declarative knowledge and procedural knowledge as articulated in the Adaptive Character of Thought (ACT) family of theories (Anderson, 1990) on human information processing and knowledge representation. Anderson's theories are based on Ryle's (1949) distinction between knowing *that* (declarative knowledge) and *knowing how* (procedural knowledge).

The paper proceeds as follows. The next section provides an overview of the conceptual foundation for this research. Following, is the methodology which includes a description of the study, experimental materials, procedures and measures. Results are presented next, followed by analyses and discussion including the study's limitations and implications. The paper ends with concluding remarks.

2. CONCEPTUAL FOUNDATION

2.1 Concept Mapping

Concept mapping techniques were developed as a means of representing the emerging science knowledge of students (Novak 1979, 1980). It has subsequently been used as a tool to support meaningful learning in the sciences and various other domains. Figure 1 shows a notation of concept maps.

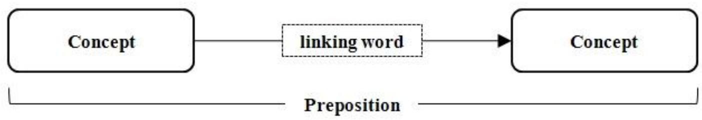

Figure 1. Concept map notation.

In Figure 1, the notation includes *concepts* and *relationships* between concepts indicated by a connecting line linking two concepts. *Linking words* or linking phrases specify the relationship between the two concepts. *Prepositions* are statements about an object or event in the universe, either naturally occurring or constructed. Propositions contain two or more concepts connected using linking words or phrases to form a meaningful statement sometimes referred to as semantic units, or units of meaning. Figure 2, shows an example of a concept map that describes the major concepts needed to understand areas of science. In that example, *The Universe contains Matter and Energy*' is a proposition. '*The Universe*', '*Matter'* and '*Energy*' are concepts, and '*contains*' is a linking word.

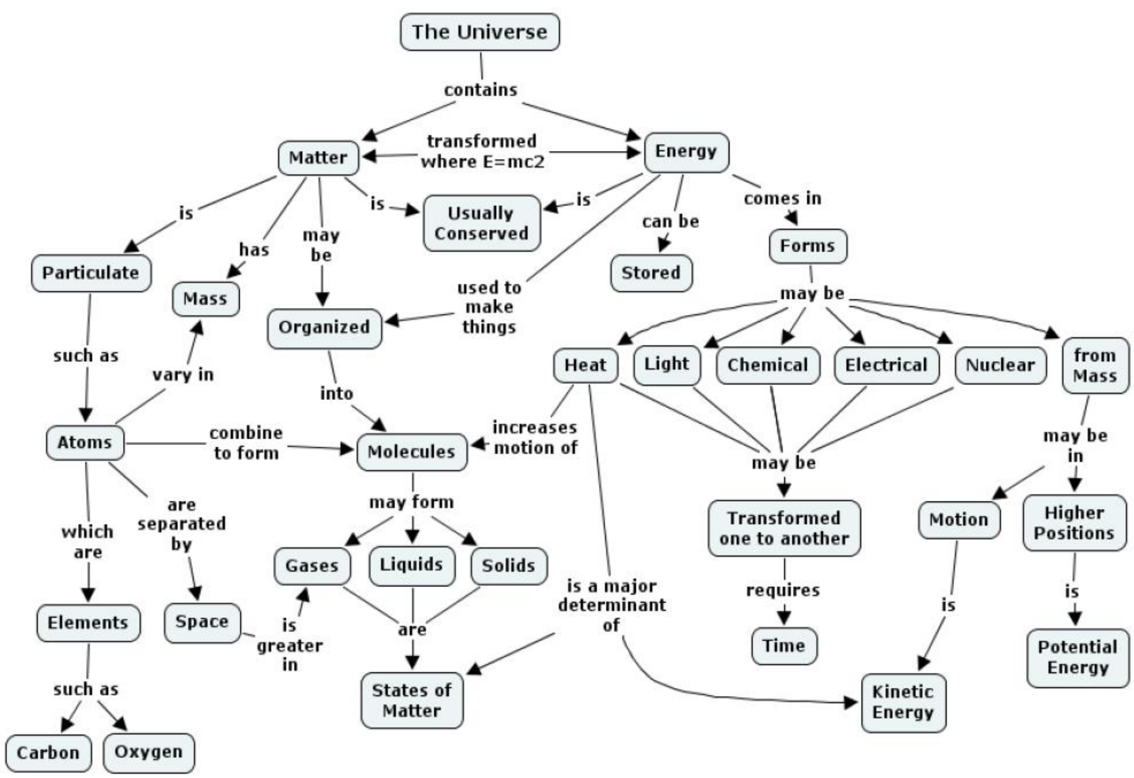

Figure 2. Example of a concept map (Novak & Gowin, 1984)

Novak's work is based on assimilation theory (Ausubel, 1978) which emphasizes the importance of prior knowledge to learn new concepts. Concept-mapping techniques are also based on the assumption that knowledge has the structure of a semantic network (Collins & Quillian, 1969). As such, concept-mapping helps students to externalize, construct and elaborate their cognitive structure. The effectiveness of concept maps has been associated with an increase in learning and knowledge retention across various instructional conditions, settings, and methodological features (see Nesbit & Adesope, 2006 for a meta-analysis).

In pedagogical contexts, the degree of pre-structure of a concept map is varied: learners are either required to construct the maps entirely by themselves (*construct-a-map*), to complete partly pre-constructed maps (*fill-in-the-map*) or to use completely pre-constructed maps (*expert-map*). Novak and his research team revealed that an *expert skeleton concept map* is one of the most helpful techniques to students (Novak & Cañas, 2008; Qin et al., 1995). Ryssel et al. (2008) investigated the effects of the three different concept-mapping techniques, *construct-a-map*, *fill-in-the-map* and *expert-map*, on promoting students' learning processes in the field of business. In that research, the *fill-in-the-map* group had the highest increase in knowledge, and the *construct-a-map* group was outperformed the expert map group.

2.2 Self-Explanation

Self-explanation is a domain-general constructive activity that engages students in active learning and insures that learners attended to the material in a meaningful way while effectively monitoring their evolving understanding. Several key cognitive mechanisms are involved in the self-explanation process that includes generating inferences to fill in missing information, integrating information within the study materials, integrating new information with prior knowledge, and monitoring and repairing faulty knowledge (Roy & Chi, 2005).

An examination of students' spontaneous self-explanations of a physics text revealed a positive correlation between the number and degree of self-explanations and student learning. In subsequent experimental studies, Chi et al. (1994) showed that students who were prompted to self-explain demonstrated greater learning gains than those who were not. Self-explanation has proven to be a successful learning strategy for multiple domains, contexts, and learners. In computer programming education, Recker and Pirolli (1992) found that improvements in skill acquisition of the Lisp programming language were facilitated by high degrees of metacognition and the use of self-generated explanation goals and strategies.

In this research, we integrate self-explanation with the concept mapping procedure as a means to increase meaningful learning performance.

3. METHODOLOGY

3.1 Participants

Sixty subjects were carefully selected for the experiment with and were also motivated by monetary reward (15,000 Won or approximately $13. US dollars each). The subjects had similar learning performance, common knowledge of basic computing programming, and no prior-knowledge of the learning topic.

Each subject was randomly assigned to one of three groups: the control group (A), the regular concept mapping group (B), and the concept mapping reinforced with self-explanation (C). Each group had twenty subjects. Table 1 describes sample characteristics (year refers to how long the subject had attended KAIST). One-way ANOVA tests indicated there were no differences of age and year between the groups (p = .335; p= 695). As a result, we are able to assume that three groups have very similar sample characteristics.

	# Males	*# Females*	*Mean Age*	*Mean Year*
Group A	12	8	22.55	3.15
Group B	14	6	21.25	2.75
Group C	14	6	21.40	2.90
Total	60		21.73	2.93

Table 1. Sample characteristics.

Beyond the sample characteristics, the subjects' prior-knowledge and skills in computer programming were accurately measured via a pre-test, which is composed of two test types: five survey questions and five fill-in-the-blank problems. Results of the pre-test indicate that the sixty subjects are equally distributed into the three distinct groups. Descriptive statistics revealed three groups have comparable pre-test scores. Furthermore, a one-way ANOVA test was conducted to assure that the three groups are equal in terms of overall prior-knowledge and skills. Tables 2 and 3 indicate that survey question scores between the three groups are significantly different (p = 0.934), and the same result is observed for fill-in-the-blank problem scores (p = 0.677). Thus, we can strongly assume that the three experimental groups have same sample characteristics and prior-knowledge in computer programming.

	Sum of Squares	*df*	*Mean Square*	*F*	*p*
Between Groups	1.233	2	.617	.068	.934
Within Groups	516.950	57	9.069		
Total	518.183	59			

Table 2. Results of one-way ANOVA test on the survey questions in the pre-test.

	Sum of Squares	*df*	*Mean Square*	*F*	*p*
Between Groups	1.233	2	.617	.393	.677
Within Groups	89.350	57	1.568		
Total	90.583	59			

Table 3. Results of one-way ANOVA test on the fill-in-the-blank problems in the pre-test.

3.2 Experimental Materials

A summarization of the materials used in the experiment is as follows:

- *Pre-test* – Test problems were designed to assess the subjects' prior-knowledge and skills in general computer programming.
- *Post-Test* – The test problems were developed to measure the subjects' newly acquired knowledge and skills in Ruby programming after a learning phase.
- *Tutorials* – A concept mapping tutorial and a Ruby programming tutorial were developed for the experiment.
- *IHMC CmapTools* – The software used for concept mapping is the Institute for Human and Machine Cognition's CmapTools; an open source software tool designed for supporting the construction of concept maps http://cmap.ihmc.us/
- *Self-Explanation Note Program* – A program was specially designed and developed to reinforce concept mapping with self-explanation.
- *Expert Concept Map* – An expert concept map is defined as a completely pre-constructed concept map generated by several experts.
- *Expert Skeleton Concept Map* – An expert skeleton concept map is defined as a partial pre-constructed concept map generated from the expert concept map. The expert skeleton concept map consists of about 20% of the expert concept map.

3.3 Experimental Procedure

The overall procedure of this experiment is described in the Figure 4. The three experimental groups were treated identically in the introduction, pre-test, learning, and post-test phases. In the post-learning phase, however, each group followed a different learning strategy:

- *Group A – Control group.* The subjects in the group studied in a conventional way without concept mapping.
- *Group B – Regular concept mapping group.* Given the expert skeleton concept map, the subjects in the group modified and extended the concept map (fill-in-the-map strategy).
- *Group C – Concept mapping reinforced with self-explanation group.* The subjects in the group started with an expert skeleton and finished with self-explanation activities (the proposed method).

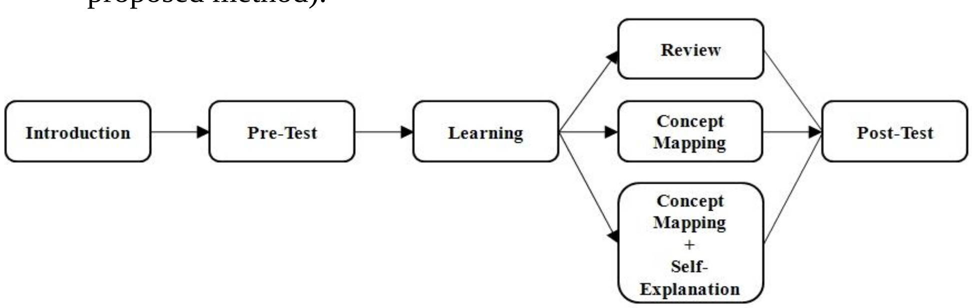

Figure 4. Overall procedure of the experiments.

A summarization of the experimental procedures follows.

- *Introduction* (15 min.) – An introduction on the experiment was presented to all subjects.
- *Pre-Test* (10 min.) – All the subjects took the pre-test.
- *Learning* (25 min.) – All the subjects read and studied the Ruby programming tutorial. Using a development environment such as IRb (interactive Ruby), note-

taking or underlining was not allowed in order to prevent the subject from acquiring more knowledge from other than the tutorial which could affect learning performance.

- *Post-Learning for the Group A* (25 min.) –The subjects in the group A (control group) used a conventional learning method. That is, the subjects just reviewed the tutorial. Again, use of IRb, note-taking or underlining were not allowed for the same reasons of the learning phase.
- *Post-Learning for the Group B* (25 min.) – The group B (regular concept mapping group) adopted the fill-in-the-map strategy, which is currently known as one of the most effective concept mapping methods (Hardy & Stadelhofer, 2006). Given the expert skeleton concept map (which contained key concepts and relationships), students were asked to add concepts to the map and restructure the map in ways that would make the most sense to them. During the concept mapping, the students are allowed to refer the Ruby programming tutorial. Using IRb, note-taking and underlining, however, were not allowed.
- *Post-Learning for the Group C* (25 min.) – The group C (concept mapping reinforced with self-explanation group) used the proposed method which is composed of two internal phases: concept mapping and self-explanation. In the both concept mapping and self-explanation phases, the students are allowed to refer the Ruby programming tutorial. Using IRb, note-taking and underlining, were not allowed. During the first fifteen minutes, the learners performed fill-in-the-map method identical to group B's post-learning method. A self-explanation phase (for 10 min.) followed the concept mapping with the expert skeleton concept map. Given the expert concept map, the learners compared their own concept map with the expert concept map, and performed the following instructions explicitly via the self-explanation note program:
    - Generating inferences to fill in missing information
    - Integrating information within the study materials
    - Integrating new information with prior knowledge
    - Monitoring and repairing faulty knowledge

Scores on the multiple choice questions in that post-test were designed to assess conceptual understanding, i.e. declarative knowledge and ranged from 0 to 10.

4. RESULTS AND DISCUSSION

Results of descriptive statistics, ANOVA, and Tukey's HSD analyses for the multiple choice questions follow. Descriptive statistics of the multiple choice questions are indicated in Table 4 below. As can be seen, the means for the group A, B and C are, respectively, 3.85, 5.05, 5.45. The standard deviations for the groups are, respectively, 1.424, 1.146, 1.05.

	N	*Mean*	*Std. Deviation*	*Std. Error*
Group A	20	3.8500	1.42441	.31851
Group B	20	5.0500	1.14593	.25624
Group C	20	5.4500	1.05006	.23480
Total	60	4.7833	1.37892	.17802

Table 4. Descriptive statistics of the multiple choice questions.

4.2 Results of the One-Way ANOVA

Results of the one-way ANOVA appear in Table 5 below and show *F* to be significant beyond the 0.01 level: $F(2, 57) = 9.359$; $p < .001$. Eta squared is 0.247 which, according to Cohen's classification (Cohen, 1988), is a large effect.

	Sum of Squares	*df*	*Mean Square*	*F*	*p*
Between Groups	27.733	2	13.867	9.359	.000
Within Groups	84.450	57	1.482		
Total	112.183	59			

Table 5. Results of one-way ANOVA test on the multiple choice questions.

4.3 Results of the Tukey's HSD

Tukey's Honestly Significant Difference Test (HSD) is the most conservative pair-wise comparison test among the individual treatment means (Klockars & Sax,1986) and is the least likely test to detect real differences between pairs of means. In the result of the Tukey's HSD test on the multiple choice scores (Table 6), the test confirms the mean difference between the groups A and B as well as the groups A and C; but the mean difference between the groups B and C is insignificant. The conservative *p*-values for the differences between means for the group A and B, A and C, B and C are, respectively, .008, < .001, .555. The differences between means for the group A and B, A and C, B and C are 1.2, 1.6, 0.4, respectively.

(I) group	*(J) group*	*Mean Difference (I - J)*	*Std. Error*	*p*
Group A	Group B	-1.20000	.38491	.008
	Group C	-1.60000	. 38491	.000
Group B	Group A	1.20000	. 38491	.008
	Group C	-.40000	. 38491	.555
Group C	Group A	1.60000	. 38491	.000
	Group B	.40000	. 38491	.555

Table 6. Results of Tukey's HSD test on the multiple choice questions.

4.4 General Discussion

Statistically significant mean differences between some groups are found from the experimental results of the one-way ANOVA and Tukey's HSD tests. The results of the one-way ANOVA tests show there is a significant difference between multiple choice scores between the groups.
Consistent with previous research (Qin et al., 1995; Ryssel et al., 2008), Tukey's HSD test on the multiple choice scores showed that the group B's score is significantly higher than the group A's score. The result means that concept mapping helps learners to understand declarative knowledge. In the Tukey's HSD test on the multiple choice scores, the mean difference between the group A and C is significant at < .001 level, which is much more significant than the mean difference ($p = .008$) between the group A and B. This confirms that the proposed method more significantly helps the learners to understand conceptual (declarative) knowledge.

5. CONCLUSION

5.1 Summary

The purpose of this research is to improve concept mapping via an integration of the concept mapping procedure with self-explanation. Although the difference between in the fill-in-the-map group and the proposed-method group are not significant statistically, interesting tendencies were identified: the mean difference between the control group and the proposed-method group is more statistically significant than that between the control group and the fill-in-the-map group. Thus, data analyses to date of the experimental results are encouraging because it reveals that our new method does in fact improve learning of declarative knowledge. Data analyses of procedural knowledge that was gathered based on a series of skill compilation tasks are currently underway and will also be presented at the conference. Overall, the results will determine if the proposed method facilitates the acquisition of knowledge and skills needed to solve complex novel problems which will be in addition to the benefits achieved from the improvements in declarative knowledge.

5.3 Limitations and Future Work

While this research demonstrated that the current concept mapping method can be improved in order to provide more meaningful learning to learners, our study does have limitations. For instance, the timing of the length of the experiment should be increased to measure learning performance more accurately. Also, the construction methods of expert concept maps as well as expert skeleton concept maps remain a controversial issue. Lastly, an effective time proportion for the concept mapping and self-explanation phases has not been suggested by the literature. In a follow-up study, we plan to increase the sample size, increase duration of the experiment and also elaborate the proposed procedures with additional theories on cognitive science and education. Lastly, in spite of the limitations of the current study, we expect that other knowledge visualization studies reinforced with self-explanation will produce results similar to what we have achieved.

References are available from the corresponding author upon request.