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Investigating the effect of using the social semantic tagging-based learning guidance on science learning

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Abstract: Enhancing prior knowledge has been recognized as an important learning strategy in enhancing the learning experience and performance for students. Past studies on enhancing prior knowledge have focused on reading materials that are manually generated by website administrators and educators. This is time-consuming and expensive process, such that prior knowledge cannot instantly correct and effective way to adaptive aid students in the learning process. To cope with these problems, this paper proposes a social semantic tagging-based learning guidance approach to obtaining relevant prior knowledge and the presented study examines the impact of using the social semantic tagging-based learning guidance on science learning. To evaluate the effectiveness of the proposed approach, an experiment was conducted by assigning 56 students to participate in this learning activity. The students in the experimental group adopted the social semantic tagging-based mobile learning approach, while those in the control group learned with the conventional mobile learning system. The experimental results show that the proposed approach not only promoted the students' learning achievements and motivations, but also improved their learning self-efficacy and socialization. The proposed approach with prior knowledge construction provides additional help for students and teachers in conducting and participating in interactive English reading learning activities.

Keywords: Ubiquitous learning, social semantic tagging, intelligent tutoring systems, interactive learning environments

1. Introduction

Reading learning can be regarded as a process of accumulating information or experience. Enhancing students' prior knowledge before reading scientific articles is becoming increasingly important for students, as it helps students learn quickly and effectively. Yang and Quadir (2018) points to a large body of research that indicates "learning proceeds primarily from prior knowledge, and only secondarily from the presented materials". Therefore, to help educators in enhancing students' prior knowledge, an effective prior knowledge recommendation and learning guidance tools play an important role to assist students in obtaining the relevant organizational prior knowledge in the learning process (Chung, Hwang, & Lai, 2019; De Medio et al., 2020).

Owing to the recent rapid developments of big data application and social network technologies, new learning technologies are continuously being developed (Shorfuzzaman et al., 2019). Applying social network analysis and semantic analysis enhanced teaching modes are becoming a widely adopted learning mode that enables learning activities to be conducted in learning tasks (Gruzd, Paulin, & Haythornthwaite, 2016; Shen & Ho, 2020). Moreover, educators are increasingly turning to Web 3.0 applications such as semantic web, social networking sites, and semantic wikis to enhance classroom learning. The emergence of Web 3.0 has not only enhanced the social semantic web use of the Internet, but also significantly changed the classroom educational experience (Songkram et al., 2019). This new learning technologies and extend learning strategy support user autonomy through increased levels of socialization and interactivity, access to open communities, and peer-to-peer networking. Previous studies have demonstrated that the social network analysis with prior knowledge construction provides additional opportunities for learning instruction (Gašević et al., 2019; Zambrano et al., 2019).

However, despite the great advantages of social network analysis with prior knowledge construction mentioned above, it is difficult to set up complex knowledge construction and personal learning recommendation to adaptive aid students in the learning process (Holland, 2019; Omodan, 2019). Therefore, it has become an important issue to develop methodologies or tools to assist students in obtaining the relevant organizational prior knowledge effectively. To cope with this problem, this study proposes a social semantic tagging-based learning guidance approach for mobile learning. Moreover, learning motivations, perceived ease of use and usefulness, and students' self-efficacy are measured to investigate the effects of the proposed approach on the in-field performance of the students from different aspects.

2. A social semantic tagging-based learning guidance approach for supporting prior knowledge recommendation

This study designs a social semantic tagging-based learning guidance approach and develops a prior knowledge recommendation system, called SSTL, which combines with social tagging and semantic concepts of articles to exploit social networking technology to improve a prior knowledge reservoir for students. Figure 1 illustrates the architecture of this approach. The definitions and the formulations of the proposed approach involve various strategies in structural analysis, semantic analysis and social network analysis. The basic ideas of each phrase and constructing process are outlined below.

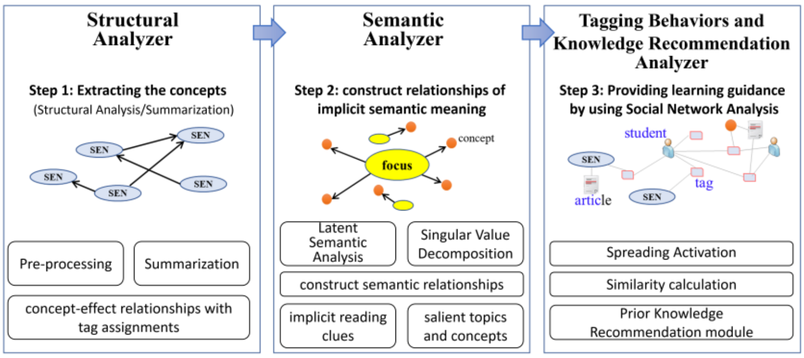

Figure 1. Flow of the SSTL interactive u-learning process.

STEP 1: Extracting the concepts from reading an article by using structural analysis

In order to help students organize ideas through tagging learning, we first considered grasping the structure of the articles and retrieving key information by using the technique of text summarization. Moreover, in the process of summarizing a reading article, the characteristics of summarization can extract the important terms and represent the meaning of the reading article. The information is useful to make students aware that the text has structure, and to provide sufficient practice in the learning process so that they can respond to those clues during the tagging process of our design. After the summarization process is carried out, each concept within the article is used to construct the concept-effect relationships with tag assignments (tag, concept, exam, and user) from individual students.

STEP 2: Using tags to construct relationships of implicit semantic meaning

After all the possible mapped concepts are found for a tag, we need to consider how to find implicit reading clues. In doing so, students' annotated tags are regarded as a medium for identifying implicit semantic meaning. Thus, we use Latent Semantic Analysis (LSA), a text-based summarization algorithm first proposed by Gong (Garrison & Anderson, 2003), to help construct the implicit semantic meaning of a text. After performing LSA, more semantic relationships can be brought into our tag scoring equation, so that the equation can provide an efficient way to extract the implicit meaning of the students' tags.

STEP 3: Providing learning guidance by using social network analysis

First, we combine above implicit meaning and topic preferences generated by integrating tag weighting and constructing a semantic similarity matrix between the tags and important concepts within the reading material to perform spreading activation (SA). Research has demonstrated that the spreading activation approach is employed in many other systems for modeling concepts that might be related (Abbasian & Farokhi, 2019). Moreover, it can help to construct semantic relationships, which are used to draw semantic inferences from a generated vector. After performing SA, the result, therefore, is the generation of all patterns of tags related to a set of article topics, which can represent a view of a learning network in the specific usage context. Meanwhile, it can be seen as a learning mechanism where the system learns from the student's tagging behaviors. Lastly, in order to discover the appropriate prior knowledge for a student, the final activation vector of the tags examine the prior knowledge database to find the most appropriate tagged article to serve as a prior knowledge supplement. The article with the highest value is then selected as the most appropriate prior knowledge article for the user.

3. A social semantic tagging-based learning environment for knowledge construction

Given the learning guidance approach of our system outlined above, this section also covers the student interface designed to assist students in obtaining the relevant organizational prior knowledge. Figure 2 illustrates the student interface of the social semantic tagging-based learning guidance system, which consists of five areas: (1) the "topics and article content" area located in the left part of the window, which provides students select a learning subject, and then the system interface for reading learning is displayed. Meanwhile, article content is highlighted, and can include the key sentence from the key sentence computation. This highlighted information provides each student with a quick and useful personal snapshot of the reading material; (2) the "tagging" area located in the upper-center part of the window, which provides students utilize the input area to create a list of tags. the interface encourages students to construct meaningful words or phrases to represent the article' ideas. The students use tags to make a clear overview in their mind for their reading. (3) the "discovering" area located in the lower-center part of the window, which helps students organize, discover interesting clues, and refine their thoughts or ideas of the reading. When students click on a given tag in the tag cloud, the system serves as a useful reference guide, as well as selects suitable prior knowledge materials for students by analyzing the characteristic of the tag cloud. (4) the "discussing whiteboard" area located in the upper-right part of the window for students. Students were given feedback from one of their peers and gives students a chance to sharpen their views on their reading, and to think more clearly about context when their own views are challenged. (5) the "quiz" area located in the lower-right part of the window.

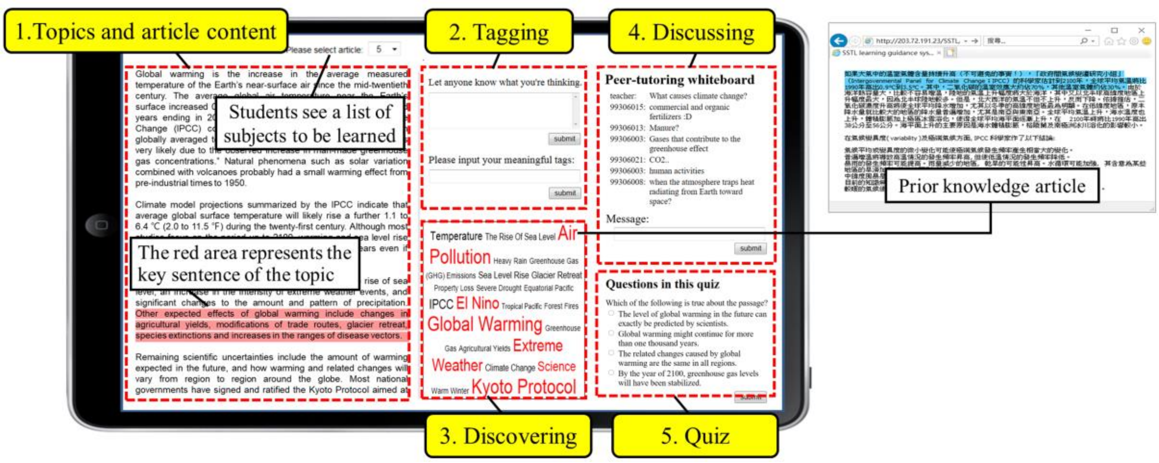

Figure 2. System interface of the learning guidance for Prior knowledge recommendation.

4. Experimental design

To evaluate the efficacy of the social semantic tagging-based mobile learning system for constructing prior knowledge, an experiment was conducted on reading activity at a senior high school in Taiwan. 56 students (24 male students and 32 female students) participated in this study. Each class consisted of 28 students. A quasi-experiment was designed by assigning the students in one class to the experimental group, and the other class to the control group. All students were taught by the same teacher who had more than ten years' experience of teaching science courses.

For material selection, reading materials in this study all pertain to science topics, and the materials were ensured to be suitable for senior high school students. In this study, the measuring tools included a pre-test, a post-test, and the questionnaire for measuring the students' learning achievements, motivations, self-efficacy, and socialization. The self-efficiency measure was developed by Pintrich, Smith, Garcia, & McKeachie (1991). The questionnaire for learning attitude measure was developed by Hwang, Yang, & Wang (2013).

Before the learning activity, an orientation was given to introduce the learning environment and the learning tasks. Moreover, the students took the pre-test and the pre-questionnaire. During the learning activity, the two classes were assigned to the control group and the experimental group. The experimental group learned with the social semantic tagging-based learning guidance embedded mobile learning, while the control group learned with the conventional mobile learning without the social semantic tagging-based learning guidance. After the learning activity, the students took the post-test and filled out the pre-questionnaire including learning motivation, self-efficacy and perceived ease of use and usefulness for comparing the learning achievements and the improvements in learning attitude of the two groups.

5. Experimental Results

5.1 Analysis of learning achievement

To evaluate the effectiveness of SSTL, pretest and posttest evaluations were implemented to demonstrate the achievement of learning outcomes. Here, the pre-test results reveal that the mean score of the experiment group was similar to that of the control group (61.61 and 62.86). The t-test result showed that these two groups did not differ significantly (t =.214, p >.05). In other words, before performing the experiment, the pre-test revealed that control and experimental group demonstrated a similar understanding of the learning topics at an alpha level of 0.05.

After participating in the learning activity, the two groups of students took a post-test. The t-test results of the post-test in Table 1 indicate that the experimental group had a higher mean score than the control group. Furthermore, the results show that the learning achievement of the experimental group was significantly better than that of the control group (t =.-3.827, p <.05). This implies that the proposed interactive u-learning system based on a social semantic tagging-based learning guidance benefited the students more than the traditional approach.

Table 1. *Paired t-test of the learning improvement for the two groups*

Variable	Group	N	Mean	S.D.	Std. Error.	t-test
Post-test	Control Group	28	59.29	12.0734	2.2817	**t = -3.827***
	Experimental Group	28	67.85	13.3531	2.5254	

$^{*}p < .05$

5.2 Analysis of learning motivations

In order to examine the difference in the learning motivation for students before and after participating in the learning activities, the questionnaire is presented with a 5-point Likert scale where '5' means strong agreement or positive feedback and '1' represents high disagreement or negative feedback. Table 2 shows the *t*-test result of the learning motivation of the two groups. The results show that the students of the experimental group improved toward learning motivation after the learning activity. In the learning motivation questionnaire, it is found the experimental group has significant difference (t=-4.26, p<0.01) between pre- and post-questionnaires. In contrast, the t-test results of the control group showed no significant difference, as shown in Table 2. This result revealed that the learning motivation of the students from the experimental group increases after the learning activity.

Table 2. *The paired t-test result of pre- and post-questionnaire of learning motivation*

Group		N	Mean	S.D.	*t*
Experimental group	Pre-questionnaire	28	3.67	0.47	-4.26**
	Post-questionnaire	28	4.14	0.35	
Control group	Pre-questionnaire	28	3.71	0.46	1.14
	Post-questionnaire	28	3.60	0.49	

**p<0.01

5.3 Analysis of learning self-efficacy

A seven-point Likert scheme was applied in the pre-test of the self-efficacy. The three sets of values in the one-way ANOVA (Analysis of Variance) test result are provided as follows: the mean value of the test was 4.21 for the SSTL enhanced Science mobile learning group and 4.14 for the Science mobile learning group. According to the results, no significant difference was shown in the self-efficacy between the two groups in the class ($F=1.42$, $p=0.25>0.05$).Based on the analysis above, this study further compared the two sets of values in the self-efficacy before and after learning groups, as shown in Table 3. The results found that the experimental group had significant difference between the pre- and post-test of the self-efficacy ($t=-3.10$, $p<0.05$). On the contrary, there was no significant difference between the pre- and post-test of the self-efficacy in the control group ($t=-1.15$, $p=0.26>0.05$). This indicated that perceived self-efficacy has been significantly improved after learning with the social semantic tagging-based learning system.

Table 3. *The paired t-test result of exercise self-efficacy of science education*

Question		N	Mean	S.D.	t
SSTL enhanced Science mobile learning group	Pre-questionnaire	28	4.03	0.42	-3.10*
	Post-questionnaire	28	4.36	0.48	
Science mobile learning group	Pre-questionnaire	28	4.14	0.52	-1.15
	Post-questionnaire	28	4.32	0.47	

*$p<0.05$

5.4 Analysis of Perceived Ease of Use and Usefulness

To better understand the students' perceptions of the use of the SSTL learning system, this study collected the students' feedback in terms of "perceived usefulness" and "perceived ease of use". Results found that most students gave positive feedback concerning the two dimensions of the SSTL learning system. The average ratings for "perceived ease of use" are 3.75 and 3.42 for the experimental group and the control group, respectively; moreover, their average ratings for "perceived usefulness" are 3.85 and 3.14. In comparisons with ratings given by the control group, it should be noted that the students in the experimental group gave higher ratings to "perceived ease of use" and "perceived usefulness", implying that the students who learned with the SSTL learning system revealed higher degrees of technology acceptance than those who learned with mobile learning system.

In terms of perceived usefulness, the t-test result ($t=4.67$, $p<0.001$) shows significant between the experimental group and the control group. It depicts that the social semantic tagging-based learning guidance approach (SSTL) is more effective than the conventional mobile learning approach. From the students' interview feedback, most students in the experimental group agreed with the usefulness of the SSTL learning system approach in improving their learning achievements. Moreover, they could learn better by using interactive learning guidance system and the learning system is helpful to their learning of science education.

6. Conclusions and future work

In this study, the impact of using the social semantic tagging-based learning guidance (SSTL) was explored to enhance the positive impact of science learning. The proposed SSTL approach and interactive u-learning system were developed that can provide a richer understanding of how users can more efficiently employ social semantic tagging to enhance the learning experience. For knowledge construction, the proposed approach provides opportunities for students to demonstrate knowledge connections, because tags as annotations can serve as spontaneous behavior in reading (Chan & Pow, 2020). The experimental results showed that the system's valuable functions for prior knowledge acquisition and reading comprehension. It was also found that the students of the experimental group had significantly improved in their learning motivation and perceptions.

Despite these encouraging experiment results however, there are still difficulties in creating a quality measurement of semantic tagging for tag-based interactive learning environments. One major problem is that tags have issues with both sparseness and noise. Before performing our experiment, this study used several preprocessing techniques to reduce the influence of sparseness, including Porter stemming and stop word. Moreover, the study also proposes a series of tag implementation guides to ensure that students tag meaningful ideas, but the filtering rule still incomplete. These results also point to suggestions and references for the design of efficient mobile-supported learning activities in the future. Additionally, the small sample size of each group is another problem. Therefore, further research with larger sample size will be needed to investigate this methodological concern and its practical applications.

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