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A tag based learning approach to knowledge acquisition for constructing prior knowledge and enhancing student reading comprehension

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A B S T R A C T

Prior knowledge is an important issue in the study of concept acquisition among students. Traditional studies on prior knowledge generation during reading activities have focused on extracting sentences from reading materials that are manually generated by website administrators and educators. This is time-consuming and strenuous, and hence personalized prior knowledge recommendation is difficult to perform. To cope with this problem, we combine the concept of prior knowledge with social tagging methods to assist the reading comprehension of students studying English. We incorporate tags into a tag based learning approach, which then identifies suitable supplementary materials for quickly constructing a student's prior knowledge reservoir. The experimental results demonstrate that the proposed approach benefits the students by embedding the additional information in social knowledge, and hence significantly improve their on-line reading efficiency.

1. Introduction

In the past, learning was considered a process of accumulating information or experience (Tang, Wang, Wang, Lu, & Li, 2011). Effective reading comprehension requires the integrated interaction of derived text information and preexisting reader knowledge (Corredor, 2006; Wang, Wang, Huang, & Chen, 2004), especially with learners of foreign languages such as English. Studies have found that strong prior knowledge of subject material enables students to attain higher comprehension, performance, and motivation. This further suggests it is important to assist students in obtaining relevant prior knowledge, as this can enable them to engage meaningfully with their learning material (Lin, Lin, & Huang, 2011). Therefore, building prior knowledge through reading is becoming increasingly important for students, as it helps students learn quickly and effectively. Meanwhile, obtaining this skill early during the learning process is also crucial. Thus, to help students make the most of new experience educators need to understand how prior knowledge affects learning (Chen & Macredie, 2010; Chi & Zhu, 2010).

However, despite the value of prior information, Taiwanese senior high schools have largely focused on skill development rather than expanding a student's knowledge of the world, such that reading comprehension and prior knowledge instruction are still a challenge in English as a foreign language (EFL) classes in Taiwan (Hsu, Hwang, & Chang, 2013). Because of Taiwan's exam-oriented education, students spend most of their time preparing for tests, and rarely have enough time to acquire knowledge from extensive personal reading or living experiences. This leads to poor levels of reading comprehension among students, such that even above average students are unable to read and fully understand material.

To cope with the problem, researchers and educators continue to seek new teaching methods. One such method includes using Web 2.0 tools to develop adaptive learning environments, and educators are increasingly turning to Web 2.0 applications such as social networking sites, blogs, and wikis to enhance classroom learning and develop a new generation of learning architecture (Chen, Chen, & Sun, 2010; Hsu, Hwang, & Chang, 2010; Kennedy et al., 2007; McLoughlin & Lee, 2008, 2010; Valenzuela, Park, & Kee, 2009). In contrast to a teacher-centered pedagogy, the focus is shifting to the observation of learning implications, the orientation of the learning process, and teacher feedback on

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student learning progress (Jha, 2005; Sun, 2011). The emergence of social tagging with prior knowledge construction provides additional challenges for learning instruction.

In response to these developments, we propose an online collaborative reading platform based on Web 2.0 social tagging techniques that allow students to annotate various online resources (materials) with freely chosen tags. Tagging certain activities can help students summarize new ideas and quickly grasp the structure and concepts of English articles (Barak, Herscoviz, Kaberman, & Dori, 2009; Chen et al., 2010; Conole & Culver, 2010; Hwang & Kuo, 2011). Moreover, these tags are also designed to enhance critical thinking skills by directing students to evaluate and then support or oppose different viewpoints on their readings. They not only facilitate students in finding and organizing online resources, but also provide meaningful collaborative semantic data which can potentially be exploited by recommendation systems (Guan et al., 2010; Rey-López, Díaz-Redondo, Fernández-Vilas, & Pazos-Arias, 2010). Meanwhile, designing prior knowledge learning environments that help promote critical thinking through article construction can activate a learner's existing schema and help them identify new information from articles more easily (Kim & Hannafin, 2011). Such background information may even help learners find clues for identifying the meanings of new vocabulary or sentence patterns (So & Brush, 2008). The most important value of this social tagging system, however, is the promise it shows for dramatically improving student reading comprehension.

Below, we present a series of research findings, theories, and empirical methods that can help such interactive experiences work more effectively with a student's prior knowledge. In our conclusion, we discuss in more detail the effects of combining our approach with Web 2.0 social tagging techniques, and its impact on English learning.

2. Developing a tag-based prior-knowledge recommendation system

The TAK (tag-based prior knowledge recommendation) system is comprised of two key components, that is, a tag-based article reading interface and a tag-based prior knowledge recommendation tool. These components help students retrieve and apply their knowledge effectively and efficiently, and improve their learning performance. Fig. 1 illustrates the architecture of the TAK system, which consists of three parts: data preprocessing, structure analysis, and personalized prior knowledge recommendation. For more details concerning the definitions and the formulations of the TAK, please refer to Appendix A.

Fig. 2 illustrates the user interface of the proposed TAK system. Students first select articles via a drop-down menu to read the context of the selected article. The article reading interface consists of three areas: 1) an article content area located in the left part of the window; 2) an area located in the lower-right part of the window for students to input meaningful words or phrases to summarize the key ideas in the article; 3) a "personal article structure" function located in the upper-right side. In a personal article structure, a root node (e.g. global warming) is used to present the main topic of the article, and several sub-nodes (e.g. air pollution, extreme weather, and Kyoto protocol) represent the sub-topics of the paragraphs in the article. If the paragraph is not important, no sub-node is included. Meanwhile, article content is highlighted whenever students click on the sub-node of the "personal article structure." This highlighted content can include entire paragraphs, any key sentence represented by the sub-node, and the key sentence from the key sentence computation. Overall, this highlighted information provides each student with a quick and useful personal snapshot of the reading material.

Fig. 3 illustrates the structure of the "network of prior knowledge," which consists of a root node and sub-nodes, and the locations of nodes that correspond to the order of the paragraphs. This structure varies depending on the student. If a node of the structure represents the recommended topic for a student, such as "Kyoto Protocol," the node is highlighted. The most important function of the network of prior

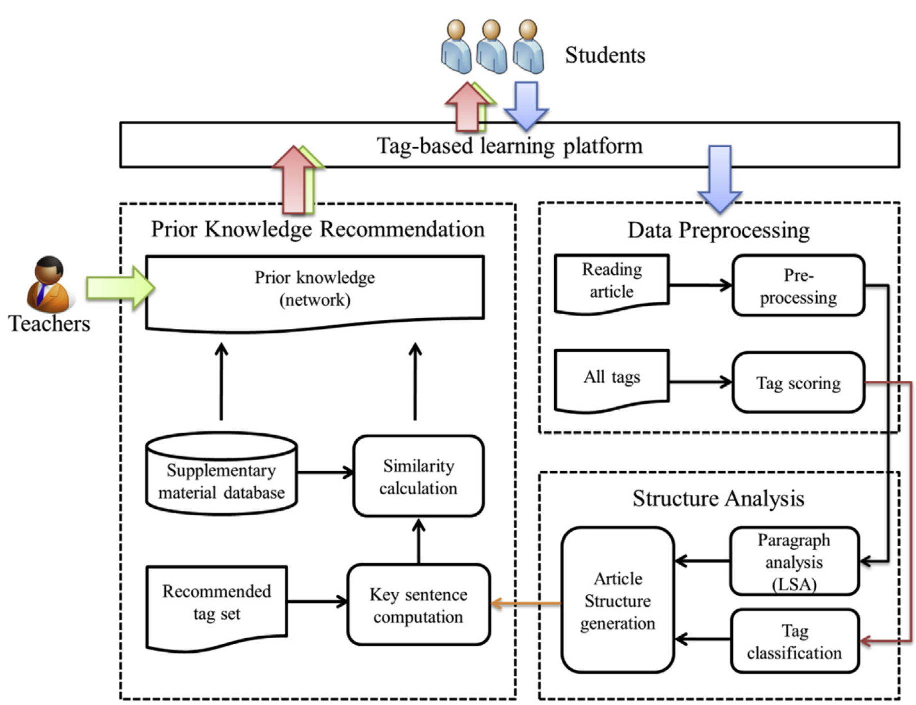

Fig. 1. Framework for the TAK system.

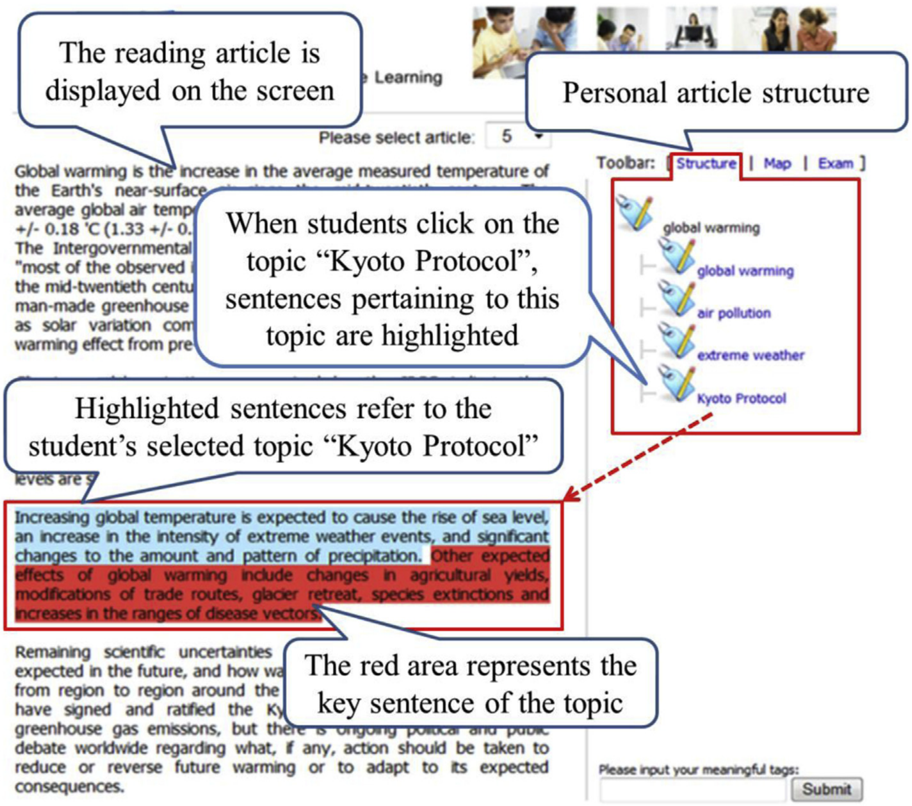

Fig. 2. Reading interface and personal article structure.

knowledge is its provision of adaptive and necessary prior knowledge. Students click any node in the prior knowledge network and a new window appears, displaying the prior knowledge article to the student, as demonstrated in Fig. 4. In this example, the provided articles are in Chinese, because the goal is to provide articles based on the students' prior knowledge to supplement their knowledge deficiencies. This can more easily assist students in enriching prior knowledge and improving their reading comprehension.

Fig. 5 shows the teacher interface presenting the current status of a student's learning performance and tagging behavior. When students who have a learning disability are diagnosed by analyzing the tag cloud, this interface can assist teachers in providing focused feedback and questions to students as soon as possible. This information is clearly helpful for assisting teachers in evaluating the reading comprehension status of students, and thus provides teachers with valuable input when they attempt to adjust teaching strategies or diagnose a student's learning obstacles.

3. Experimental design

To evaluate the effectiveness of the proposed approach, an experiment was conducted on reading activity at a senior high school in Taiwan. The objective of the learning activity was to improve student comprehension, translating into overall better English performance.

3.1. Experiment procedure and participants

Fig. 6 shows the experiment procedure of this study. The participants were sixty students from two classes of first year students at a senior high school in Taiwan. One class was assigned to be the control group and the other was assigned to be the experimental group (each with 30 students). The two groups of students did not have any interaction, so that they would not be affected by the other group during the reading learning activity.

The pre-test and post-test were designed to evaluate the learning effectiveness of the students. All of the test items had been validated by a domain expert who had more than ten years' experience in teacher education at the senior high school level. The two groups of students took a pre-test at the beginning of the experiment. Moreover, the pre-test was used to check for differences in prior knowledge between the control and experimental groups.

After the pre-test, it took four weeks, 100 min per week, to conduct the learning activity. The students in the experimental group were directed to use this TAK system. The students received the reading materials and learned with the proposed approach for improving their English reading comprehension. Moreover, the students in the control group received the same reading materials and used the regular on-line reading process without providing students with any tag-based prior knowledge (TAK) guidance.

After finishing the learning activity, all of the students took a post-test. A post-test was used to test for differences in improvement in reading comprehension ability between the control and experimental groups. All students were also asked to fill out a questionnaire (with

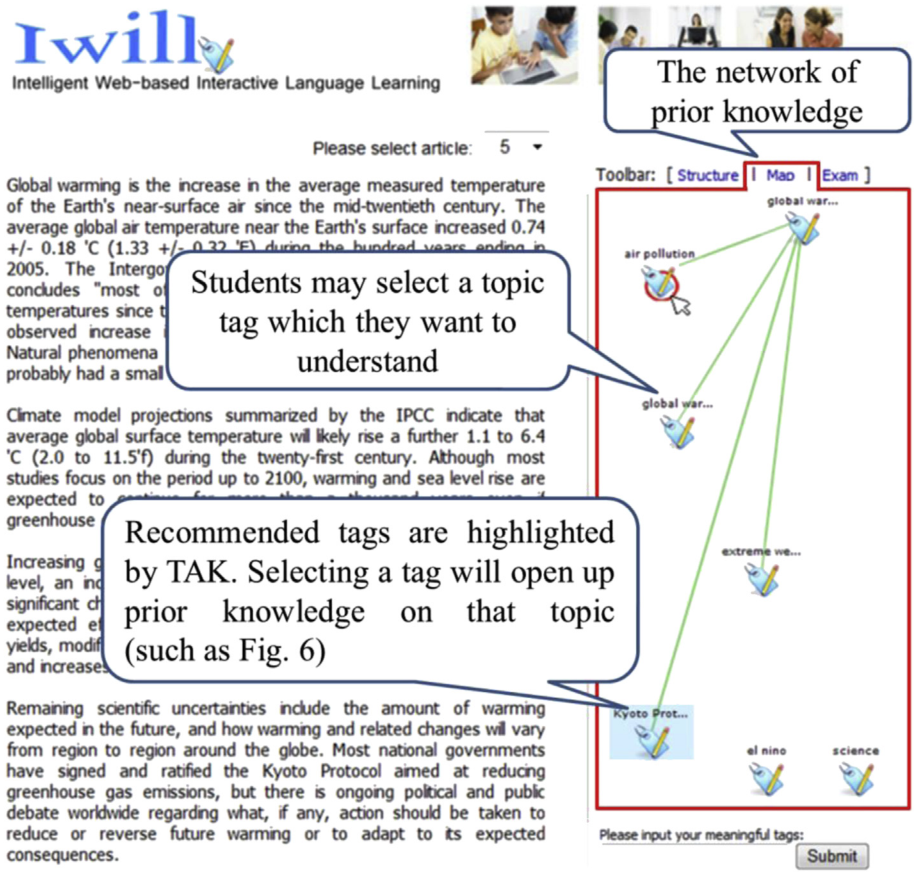

Fig. 3. Reading interface and network of prior knowledge.

five scale rating scheme) to help understand their learning behavior, system usage, and satisfaction with our system. Moreover, a total of five teachers at the senior high school in Taiwan were invited to evaluate the quality of novel recommendations for the proposed TAK system.

3.2. Material selection

Because prior knowledge is usually specific to subject matter, it is difficult to state general facts about prior knowledge across all areas of human interest (Roschelle, 1995). Moreover, past studies have found that science article content is more difficult to ground in everyday experiences compared with social or history material, and thus prior knowledge is more critical. Therefore, reading materials in this study all pertain to science topics, such as global warming, energy alternative, and biology. These materials were selected from the College Entrance Examination Center (CEEC) to ensure that the materials are suitable for senior high school students.

4. Results

4.1. Tag recommendation performance comparison

The objective of this subsection was to evaluate the overall effectiveness of the proposed tag recommendation approach by comparing them with the recommendation approaches that are based on the ratings and tag information.

For the evaluation we have select 30 articles. The selected articles are based on a series of domain-specific topics, for example “biology”, “alternative energy”, and “global warming”, that were chosen by the experts to ensure that they possessed the necessary expertise to judge the relevancy of the recommended tags in context of the article. Finally, we have divided the article pool in a training set and a test set. For training we used 24 articles and the test set consists of 6 articles. We used the training set to tune the parameters of the TAK approach.

Additionally, the ground truth is manually created through a blind review pooling method. The top 10 recommendations from each of the four recommendation approaches were taken to construct the pool. Three experts were invited to complete the evaluation. The experts were then asked to assess the descriptiveness of each of the recommended tags in context of the article. To help them in their task, the experts were presented the article, tags, content of the article and students’ comments. They could access and view the article directly, to find additional context through Internet when needed. The experts were asked to judge the descriptiveness on a four-point scale: very good, good, not good, and don’t know. The distinction between very good and good is defined, to make the evaluation task conceptually easier for the user. For the evaluation of the results, we will however use a binary judgment, and map both scales to good. In some cases, we expected that the expert would not be able to make a good judgment, simply because there is not enough contextual information, or when the expertise of the expert is not sufficient to make a motivated choice. For this purpose, we added the option (don’t know).


Intelligent Web-based Interactive Language Learning

拋開京都議定書，繼續前進 - 政策制定者必須建立一個條約架構，期限延伸到本世紀末，來處理全球氣候變遷問題。
Moving beyond Kyoto
作者/薩克斯（Jeffrey D. Sachs）
譯者/林筱雯

2006年底發生了幾件事，使得美國和其他國家更可能進行正式全球協商，來控制溫室氣體的排放。因此，這正是發問的好時機：一份有意義的全球協議必須包含什麼？1992年聯合國氣候變遷綱要公約是一個好的開始，這是一份國際條約，強制簽署國必須採取行動，因應氣候變遷。京都議定書也是條約規範的特殊因應措施之一。氣候變遷綱要公約的簽署國（包括美國和幾乎全球其他所有國家）聲明其目標是「使大氣中的溫室氣體濃度穩定維持在最低限度之內，防止氣候系統受到危險的人為干擾。」京都議定書在1997年正式通過，但並沒有完全發揚氣候變遷綱要公約的精神，因為它用短期觀點來看長程目標，不夠清晰、也不夠可信，因而逐漸失去了各國的支持。解決的方法是，拋開它，繼續前進。

京都議定書要求高所得國家、前東歐共產國家，以及前蘇聯，在2012年之前降低溫室氣體排放量，目標是比1990年的排放量減少6%。這項承諾比什麼也不做好太多了（例如美國布希政府毫無因應政策），然而，它還是有兩個重大缺陷：第一，開發中國家並不受京都議定書規範，而他們的溫室氣體排放量很快就會超過全球總量的一半以上，如果中國、印度和其他開發中國家不主動參與，就不可能穩定溫室氣體排放量；第二，京都議定書把穩定溫室氣體濃度的長程目標轉變成短期的減量目標，卻沒有清楚說明兩者之間的關係。要保持排放量的穩定，必須長期改進工業技術，所需時間超過了京都議定書中2012年的期限。

我們最好盡快開始用長期眼光來看這個問題。在大氣中的碳濃度達到450~550ppm（ppm為每百萬分之一）時，「危險的人為干擾」非常可能發生。按照目前世界使用能源、砍伐森林，以及工業成長的速度，在本世紀末之前，大氣碳濃度很容易就會增加到「危險」範圍的兩倍。英國財政部剛發表的《史登報告》中，清楚說明了濃度繼續增加的災難性後果：冰原融化，使海平面大幅上升；農作物大量歉收；疾病傳播更迅速；對生態系服務也可能有重大的不良影響。

因此全球應該協議，把溫室氣體濃度保持在450~550ppm之間（我的同事氣候學家韓森認為應當採取高標準：450ppm，其他人則支持550ppm）。我們應該設定一個本世紀中的40年減量目標（例如比預期濃度低50ppm），讓它和本世紀末的目標一致。當發現新科學證據時，目標可以隨時修正。一旦我們設定好兩個長期目標，全球各政府也能採取各種措施來達成，措施可以包括：以市場誘因來降低排放量；擴大研究永續能源利用、土地利用和工業發展；或由富裕國家轉移技術給貧窮國家。

《史登報告》中說得很清楚，採取行動來控制排放量的費用，遠低於什麼都不做的代價。低成本、高收益的努力，至少在三個領域非常可能實現：改進能源使用效率、溫室氣體排放量更低的能源工業，以及永續土地利用。智慧科技或許能夠把穩定溫室氣體濃度的長期年均花費，控制在全球國內生產毛額的1%以下。富裕國家可協助貧窮國家引進所需的科技。

所以，現在正是設定合理長程架構的時候，讓所有國家都能參與。目前的全球經濟狀況准許我們這麼做，美國新國會也做好了支持控制排放量的準備，在2008年美國總統大選之後，幸運的話，甚至更快，白宮也將支持新的條約架構。

本文的完整英文版可以在www.sciam.com/ontheweb線上閱讀（本文出自SA 200702）

Fig. 4. A popup window of a prior knowledge article.

With respect to evaluation metrics, we adopted three metrics that capture the performance at different aspects:

(1) **Mean Reciprocal Rank (MRR)** MRR measures where in the ranking the first relevant tag is returned by the system, averaged over all the articles. This measure provides insight in the ability of the system to return relevant tag at the top of the ranking.
(2) **Success at rank *k* (S@N)** we report the success at rank *k* for three values of N: S@1and S@5. The success at rank *k* is defined as the probability of finding a good descriptive tag among the top N recommended tags.

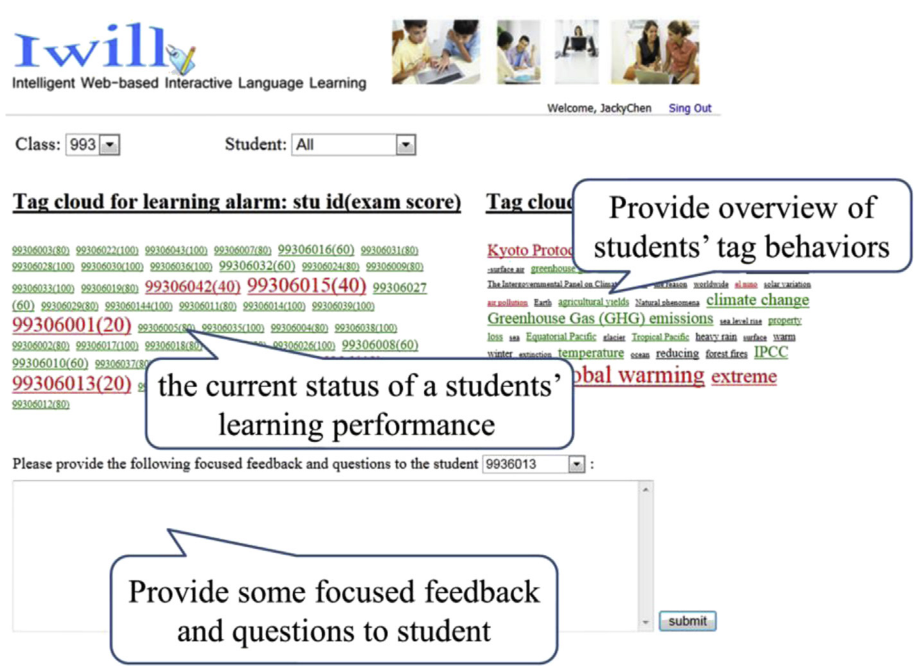

Fig. 5. Teacher interface for browsing students' portfolios.

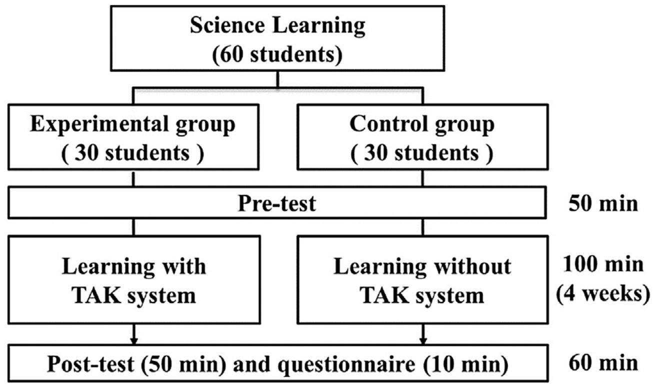

Fig. 6. Experiment procedure.

(3) **Precision at rank *k* (P@N)** we report the precision at rank 5 (P@5) and 10(P@10). Precision at rank *N* is defined as the proportion of retrieved tags that is relevant, averaged over all articles.

Finally, we compared the above metrics of the recommended top 20 tags produced by the following approaches:

- TF-idf: term frequency–inverse document frequency, is a numerical statistic which reflects how important a word is to a document in a collection.
- Tag tf-idf: In this approach proposed by Diederich et al. (2006), the tf-idf tag profiles were used to represent users' topic preferences.
- CF-Tag: is the tag based collaborative filtering (CF) approach based on the User-Tag relationship or the binary User–Tag matrix. The similarity of two tags was calculated based on the overlap of their user sets (i.e. the Tag-User mapping). In our experiments, an advanced version of CF that takes the inverse tag frequency value of each user into consideration to measure the similarity of two tags was implemented as suggested by Breese, Heckerman, and Kadie (2008).
- FolkRank: is a graph-based iterative method in the spirit of PageRank that can be used for tag recommendation (Hotho, Jäschke, Schmitz, & Stumme, 2006a, pp. 111–114; Hotho, Jäschke, Schmitz, & Stumme, 2006b, pp. 411–426). It computes a PageRank vector from the tripartite graph of the folksonomy. This graph is generated by regarding User $\times$ Resource $\times$ Tag as the set of vertices. Edges are defined by the three two-dimensional projections of the hyper-graph, RT, UR and UT. The FolkRank vector is taken as one with a preference vector. Tag recommendations are generated by biasing the preference vector towards the query user and resource (Gemmell, Schimoler, Christiansen, & Mobasher, 2009; Jäschke, Marinho, Hotho, Schmidt-Thieme, & Stumme, 2007, pp. 506–514; Kim & El-Saddik, 2011).
- TAK approach, which is the proposed approach that combines implicit meaning rating and topic preferences generated through integrating tags weighting and WordNet hierarchy.

Table 1 shows the results for the four recommendation approaches on the test collection. Based on the metric success at rank 1 (S@1), we observe that for more than 38% of the cases our best performing tag recommendation strategy. For the success at rank 5 (S@5), we see that this percentage goes up to 78%. For the precision at rank 5 (P@5), we measure a precision of 0.58 for the TAK tag recommendation strategy, which indicates that on average for this strategy 50% of the tags recommended are considered useful, even reach 70.3% at rank 10. We can thus safely argue that the TAK tag recommendation strategy performs very well and would be a useful asset for students who want support when tagging their articles. As mentioned in previous section, tags hold the 3-dimensional relationship between users, articles and tags. The use of tags has shown to increase the interconnectivity amongst users and articles. Applying user tags or terms alone does not exploit the characteristic of tags correctly. Hence, attaching tags to term frequency–inverse document frequency, such as tag tf-idf, does not significant improve the performance at all. The tags are then only seen as noise. This also reflects extended the CF algorithms with tags.

Furthermore, the experimental results show that the TAK (the proposed tag based recommendation approach) not only can perform significantly better than the FolkRank, but also can demonstrate knowledge connection, as well as find more extended and meaning of the reading article. Both performed better than the other approaches. Thus, the results suggest that the proposed tag representation approach (TAK) is effective.

4.2. Analysis of learning performance

To evaluate the efficacy of the novel approach, an experiment was conducted from March 2011 to May 2011 on the English course taught at a senior high school in Taiwan. Table 2 shows the *t*-test values for the pre-test and post-test results. Here, $|t| = 1.1013 < t_{\alpha}(30) = 1.697$, which implies that the performance of the control and experimental groups in the pre-test is not significantly different. In other words, before performing the experiment, the pre-test revealed that the control and experimental groups demonstrated a statistically equivalent 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. According to the mean value of the post-test in Table 2, the experimental group performed better than the control group. The experimental group achieved significant improvement compared to the control group ($|t| = 2.938$, $p < 0.01$). Therefore, the experimental results implied that the tag-based recommendation approach (TAK) was more helpful to the students in improving their learning achievement in science learning environment.

Although experimental results demonstrated that learning performance was significantly improved, a major drawback of prior knowledge learning methods in the past still is that students must spend significant time on reading prior knowledge articles; that is, they

Table 1
Evaluation results for our tag recommendation strategies.

Method	MRR	S@1	S@5	P@5	P@10
Tf-idf	0.4288	0.2222	0.5000	0.2444	0.2865
Tag tf-idf	0.4834	0.3536	0.6421	0.4000	0.4611
CF-Tag	0.4519	0.3245	0.6439	0.3444	0.5282
FolkRank	0.5103	0.3778	0.7222	0.4130	0.4667
TAK	0.7207	0.5319	0.7835	0.5815	0.7038

are unable to learn in an efficient manner (Conrad, 2008; Duke & Pearson, 2002; Roschelle, 1995). To examine this problem, we collected data on the total time of the reading process, and analyzed individual students' time spent on learning with the TAK system. The experimental results shown in Fig. 7 reveal that students' learning time are not significantly increased by using the TAK approach, implying that the approach is efficient.

4.3. Analysis of satisfaction with system

At the end of the experiment a questionnaire was administered to the students to assess their attitudes toward the TAK system. To examine the internal consistency and content validity of this survey, Cronbach's alpha coefficient was calculated for the 20-item questionnaire (see Appendix B for the questionnaire). Moreover, we applied a discriminate validity test by using factor analysis to examine each question item. Table 3 reveals five factors among these items. The eigenvalues of the five factors are greater than 1.00 with variance 73.35% explained. From the experimental results, it was found that some question items, were not correlated with factors (that is, their load was less than 0.5). As a result, two question items were dropped, reducing the overall number to eighteen. In addition, the experiment shows that the internal reliability indexes of the five factors are 0.725, 0.817, 0.837, 0.857, and 0.916, respectively. The alpha coefficient is 0.895 after deleting the non-correlated factors. Therefore, these coefficients suggest that these factors were sufficiently reliable for representing student tagging behaviors, when the Cronbach's α is higher than 0.7 (Chen et al., 2010; Hwang, Tsai, Tsai, Tseng, & Judy, 2008).

The results of 30 effective questionnaires were then examined, with respondent scores ranging from 1 to 5 (strongly disagree, disagree, neutral, agree, and strongly agree). The major findings are presented as follows:

(1) Most of the students agreed that the TAK system is capable of helping them easily comprehend the context of reading articles, and can help them improve their reading efficiency.
(2) 93% of students thought that activating prior knowledge can help students summarize new ideas and quickly grasp the structure and concepts of English articles. Some students indicated that these tags can help them easily realize new information from the article, and that they even used the prior knowledge clues to guess the vocabulary or sentence meaning.
(3) 91% of students indicated that using tags was easy, and that is was easy to translate the context of the original article into their own words.
(4) 85% of students found that the novel system was easy to use, and only a few did not perceive usability.
(5) 87% of students thought that article structure can help them quickly grasp the main point and structure of the article. Some students indicated that the topic term is clear and sufficiently representative to grasp the meaning of a paragraph.

4.4. Results of the expert consensus survey

To evaluate the validity of the TAK recommendation quality, an experiment has been conducted by arranging five experienced experts. The experts were asked to rate importance and feasibility for TAK recommended prior knowledge based on their knowledge of the literature using 10 point scales. The rating of 10 represents the highest representative.

For compiling the expert opinions of teachers, this study employs the Delphi method, which is a reliable qualitative research method with potential for use in group-consensus research and in a wide variety of other areas (Cochran, 1983; Wen & Shih, 2008). In this method, researchers use multiple rounds of questionnaires to collect data until expert consensus of opinions emerges. In this study, the first-round of questionnaire is collected in the form of answers and elicited individual opinions from the five teachers. The expert rating interval ranges between 0 and 10, with large value signifying that the teachers believed student comprehension to be high. The next round of questionnaires is conducted after a summary of results from the previous round is shown to each expert. The Delphi procedure is completed when group-consensus or stability is gained (Murry & Hammons, 1995), and in this case, the survey lasted five rounds.

From the experimental results, it was found that a consistent consensus value with the experts' experience and opinion was 8.3, meaning that the content of the recommendation fits the scoring process of the domain experts. That is, the results demonstrate that the

Table 2
Paired *t*-test of the pre-test and post-test results.

Test	Group	*N*	Mean	SD	*t*
Pre-test	Experimental Group	30	52.7778	19.7364	1.013
	Control Group	30	47.7778	22.0949	
Post-test	Experimental Group	30	59.0000	23.0247	2.938**
	Control Group	30	43.3333	27.0164	

**$p < 0.01$.

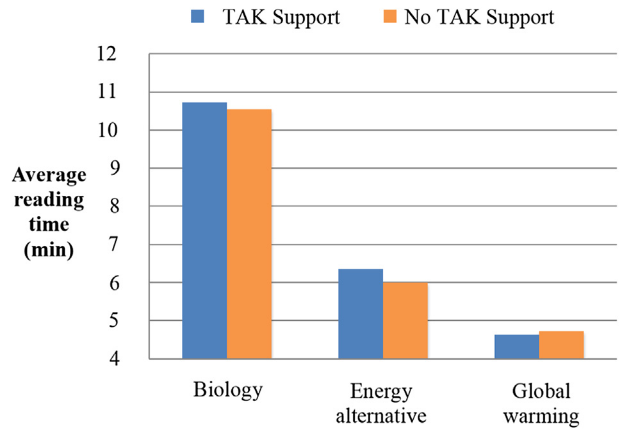

Fig. 7. Average reading time with and without TAK.

recommendation mechanism of TAK system is valid, and thus the proposed TAK approach serves as a useful tool for assisting teachers with student literacy assessment.

5. Discussion

Despite these encouraging experiment results however, there are still difficulties in the validity of our research design and the quality measurement of social tagging for tag-based learning environments. These difficulties are discussed below.

(1) This study is limited to scientific articles. Thus, further studies are still underway considering additional factors for other reading topics, which could further refine the material selection process.
(2) Additional problems concern the small size of our pool of experts. While only having five teacher/expert opinions makes it difficult to precisely measure this variable within our research, this situation was unfortunately unavoidable, as only five teachers within our participating high school had the subject matter knowledge needed to provide expert assessments of the reading material we used in our experiment. Further research is needed to investigate this methodological concern and its practical applications.
(3) Data sparseness refers to problems with users not applying any tags at all to certain sections or articles, especially those articles that are common, too new, or uninteresting. Despite this study used several preprocessing techniques to reduce the influence of sparseness, including Porter stemming (Porter, 1980) and stop word, tags still have issues with both sparseness and noise. Thus, in order to improve the performance of recommendation mechanism, one future solution to this problem is to expand tag relationships and investigate the clustering algorithm to filter out noisy tag neighbors in order to get appropriate recommendations for students. Moreover, increasing the efficiency of technologies would provide a different dimension, with regards to student-teacher and student–student interaction (Uzunboylu, Bicen, & Cavus, 2011).

Table 3
Rotated factor loadings and Cronbach's α values for five factors.

Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1: Usefulness of the article structure $\alpha = 0.725$					
I_1	0.521				
I_2	0.736				
I_3	0.576				
I_4	0.834				
Factor2: Usefulness of the network of prior knowledge clues $\alpha = 0.817$					
I_5		0.817			
I_6		0.794			
I_7		0.690			
I_8		0.773			
Factor 3: Usefulness of the TAK system $\alpha = 0.837$					
I_{11}			0.714		
I_{12}			0.687		
Factor 4: Usefulness of tagging $\alpha = 0.857$					
I_{16}				0.623	
I_{17}				0.772	
I_{18}				0.750	
Factor 5: TAK system is easy-to-use $\alpha = 0.916$					
I_{19}					0.902
I_{20}					0.824
I_{21}					0.851
I_{22}					0.757
I_{23}					0.686

Overall 30 effective questionnaires, $\alpha = 0.895$, total variance explained is 73.35%.

(4) Lastly, we expect that a more meaningful semantic structure could be extracted, by extending our approach to accumulating more learning experiences, more functions, and deeper qualitative analysis of our collected data. One future solution is to create a tag discussion forum where students can debate the appropriateness of a tag for prior knowledge articles (Gupta, Yin, Han, & Li, 2010). For future work, we plan to extend our approach to include these improvements.

6. Conclusions and future work

This study provides a new effective learning method for students, based on gathering tags to exploit human knowledge of article structure. Thus, it is distinct from past research that solely apply statistical or probability models. In doing so, this study extends the application of social tagging by designing a tag-based prior knowledge recommendation and article reading system (TAK) to provide opportunities for students to interpret article contents and find knowledge connections. The experimental results demonstrate that the proposed system can effectively assist the students in enriching prior knowledge and raise their reading comprehension. Moreover, TAK system is also helpful in assisting teachers in evaluating student reading comprehension by tag-cloud visualization. Therefore, in this study, the emergence of social tagging with prior knowledge construction provides additional help for teachers and students in conducting and participating in article reading activities.

In the near future, we will try to apply this approach to other learning applications, including foster students with different types of knowledge or competences, automatically monitor running activities and student status; moreover, we plan to develop other interactive tools, which provide students an engaging way to reinforce meaningful topics, identify suitable supplementary materials, and helps students reevaluate their reading process.

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Appendix A. Definitions and formulations of the prior knowledge recommendation mechanism

A.1. Paragraph analysis stage

The main objective of this stage is to identify significant subtopics and use Latent Semantic Analysis (LSA) to measure the importance of each paragraph and the relationship between paragraphs. After performing LSA, these important topics are described by a term–paragraph association matrix (P).

The entry of **P** is the weight of specific term in paragraph, computed by using the well-known TF-IDF term weighting scheme (Chen & Chen, 2008; Karen, 1972). The matrix $\mathbf{A} = \mathbf{P}^{\mathbf{T}}\mathbf{P}$, called a paragraph association matrix, is a symmetric matrix in which the entry is the inner products between all pairs of columns of the matrix P. As a column of P is the term vector of a paragraph, **A** represents the inner-paragraph association. This is similar to the traditional method for applying the Singular Value Decomposition (SVD) for matrix **A**: $\mathbf{A} = \mathbf{V}\boldsymbol{\Sigma}\mathbf{V}^{\mathbf{T}}$

V is an $n \times n$ column-orthogonal matrix that its columns are the orthogonal eigenvectors of $\mathbf{A}\mathbf{A}^{\mathbf{T}}$; $\mathbf{V}^{\mathbf{T}}$ is a transposition matrix of **V** and its columns are orthogonal eigenvectors of $\mathbf{A}^{\mathbf{T}}\mathbf{A}$ (it is also the right singular matrix of matrix **A**).

In other words, symmetric matrix **A** is decomposed into the sum of n matrices spanned by its eigenvectors. We can choose the first K ($K < n$) significant eigenvectors of **A** as the theme of the article, and the value of diagonal elements in $\boldsymbol{\Sigma}$ represents the significance level of the eigenvector. After matrix **A** is decomposed into **V**, $\boldsymbol{\Sigma}$, and $\mathbf{V}^{\mathbf{T}}$ with the first K significant eigenvectors of **A**, we multiply them together to find matrix $\mathbf{A}'$, where the entry $a_{i,j}$ indicates the correlation between paragraphs with top K significant subtopics. Furthermore, the diagonal element indicates the importance or representativeness of specific paragraph i in the article: $\mathbf{A}' = \mathbf{V}_K \boldsymbol{\Sigma}_{\mathbf{K}} \mathbf{V}_{\mathbf{K}}^T$.

A.2. Tag classification stage

To distinguish the difference of each paragraph, we consider tag preferences that include three types of tags from different properties of tagging behavior: topic tags, overusing tags, and common tags (Braun, Kunzmann, & Schmidt, 2010; Gupta et al., 2010; Tian, Gao, Zhang, & Zhang, 2011). This process selects the weighted tags to represent a specific student. For example, students can use a tag to represent that topic, theme or idea. When only one tag is used for a paragraph, that tag then serves as the topic of that paragraph, and is categorized and weighted as a topic tag. The topic tag acts as a kind of summary, and offers the reader an insightful view of the student's main ideas for the following paragraph. Although most paragraphs should have a topic sentence, there are a few situations when a paragraph might not need a topic sentence. Moreover, students might use the same tag repeatedly throughout an article, making it ubiquitous. In these cases, such "overusing tags" lack distinctiveness, and can induce bias within our analysis. Thus, within our scoring system "overusing tags" are first scored as zero. To remedy the shortcomings of overusing tags, we advocate using collaborative filtering (Herlocker, Konstan, Terveen, & Riedl, 2004) to identify high-quality tags for students in next stage, leveraging the collective wisdom of students. This enables efficient recovery of the tagged items distinctiveness (Xu, Fu, Mao, & Su, 2006). Lastly, a final tag type, common tags, is used to denote key points that still represent useful information in the article, despite not representing an article or paragraph's topic. Unlike overusing tags, these tags are still weighted within our scoring system. The modified tag score $W_j^{k,i'}$ is defined as:

$$W_j^{k,i'} = \left\{ \begin{array}{ll} W_j^{k,i} + Max\left(W^k\right) & , Dist(j) = 1 \\ 0 & , Dist(j) \geq |P| \\ W_j^{k,i} & , otherwise \end{array} \right\}$$

where $W_j^{k,i'}$ represents the score of the j_{th} tag of the i_{th} paragraph in the k_{th} article, $W_j^{k,i}$ represents the sum each participant's score of the same tag j, Max(W^k) represents the maximum tag score of the k_{th} article; the paragraph matrix $P = \{p_1, p_2 \ldots, p_i\}$. Dist(tag) represents the number of distribution of specific tag that appears in paragraphs.

Then, the modified tag score is used for article structure generation and similarity calculation, which is a useful factor for determining the difference of each paragraph.

A.3. Article structure generation stage

The outcome of paragraph analysis and tag classification is regarded as the evaluation of the importance of a paragraph and can help us to construct the article structure. In this section, we combine the results of paragraph analysis and tag classification to decide which paragraphs are most relevant and which paragraphs represent subtopics of the article. After filtering unimportant paragraphs, we identify the main-idea statement of every paragraph that serves as a subtopic of the article.

When identifying relevant paragraphs and their corresponding complements within an article, we denote $G = (V, E)$ as the graph of an article, with vertex set $V = \{p_1, p_2 \ldots, p_n\}$ and link set $(p_g, p_h) \in E$ if there is a link from paragraph g (p_g) to paragraph h (p_h). The vertex is considered important if important vertices point towards it, just like the voting or recommendation among vertices. If the importance of p_g is weaker than the relation between paragraph g and h, then p_g points to p_h within the graph (namely, p_g is the complement of p_h). The basic idea is a numerical weighting to each element of a hyperlinked set of paragraphs, with the purpose of measuring its relative importance within the set of paragraphs. The score of paragraph relation (PR) for paragraph g is defined as:

$$PR\left(p_g\right) = \frac{1-\alpha}{N} + \alpha \sum_{p_h \in M\left(p_g\right)} \frac{PR(p_h)}{L(p_h)}$$

where α is a damping factor that ranges from 0 to 1, $M(p_g)$ is the set of vertices that point to p_g, $L(p_h)$ is the number of outbound link that vertice p_h point to others vertices, and N is the number of vertices. The damping vector indicates that each vertex has a probability of $(1-\alpha)$ to randomly jump to another vertex within the graph. The scores are obtained by running equation $PR(p_g)$ iteratively until convergence is achieved.

After we obtain the representative score of each paragraph, we label each tag according to the rules described above (i.e. the modified tag score $W_j^{k,i'}$) and then we sum the modified tag score of each paragraph. We total the representative score and modified tag score for each paragraph via the equation below:

$$B_{k,i} = \frac{PR\left(p_{k,i}\right)}{\max\limits_{1 \le i \le n}\left\{PR\left(p_{k,i}\right)\right\}} + \frac{\sum_{j=0}^{m} W_j^{k,i'}}{\max\limits_{1 \le i \le n}\left\{\sum_{j=0}^{m} W_j^{k,i'}\right\}}$$

A.4. Personalized tag recommendation stage

Before identifying appropriate prior knowledge for a student, we recommend personal tags to each student. The basic idea of our recommendation approach is collaborative filtering (CF). The underlying assumptions of CF are that people with similar interests will prefer similar items, and that those individuals who agreed in the pass tend to agree again in the future (Konstas, Stathopoulos, & Jose, 2009; Zhen, Li, & Yeung, 2009). Meanwhile, personal tag recommendation include those that use tag information to enhance traditional algorithms used in recommender systems and those built from scratch by using the information associated with tags.

When students read an article, they apply tags to words or phrases, which helps determine what the students focused on while reading. We compare these tags with the topic tag set. Based on how well students' tags match topic tags, we will recommend topic tags that they chose note to label. For example, we assume that the two articles Doc1 and Doc2 are similar. Moreover, the similarity of the articles is determined by the fact that Doc2 shares similar characteristics to Doc1, which students A and B have already read and tagged. Thus, the recommendation tag t1 of Doc2 will be recommended to A, because she didn't label t1 in the similar article Doc1. Likewise, tag t2 will be recommended to B following the same logic. These tags represent subtopics and main ideas of the article; by recommending these tags to students, then help readers understand and identify key ideas within the reading.

A.5. Key sentences computation stage

To find suitable prior knowledge for a student, we use the key sentence of the paragraph as a query to search for similar articles. In order to ensure that these prior knowledge articles are suitably useful for students, we search for topic sentences from each paragraph that the student is unfamiliar with or does not understand.

Key sentences are selected by comparing the similarity between every sentence and the tag set (i.e. topic tags and recommended tags). We then present these paragraph topic sentences along with the article to the student. This process is shown below.

$$W_e^k = \sum_{j=1}^{m} W_j^{k,i'} \times W_j$$

$$W_j = \begin{cases} 1, & T_j^{k,i} \in \left\{ TR_i \cap S_e^k \right\} \\ 0, & T_j^{k,i} \notin \left\{ TR_i \cap S_e^k \right\} \end{cases}$$

where W_e^k is the tag score in the e_{th} sentence of the k_{th} article; $W_j^{k,i'}$ is the modified tag score of the j_{th} tag of i_{th} paragraph in the k_{th} article; $T_j^{k,i}$ represents the j_{th} tag of the i_{th} paragraph in the k_{th} article; TR_i is the set of tags, including the topic tag of the i_{th} paragraph and recommended tag of each student; S_e^k is the word set in the e_{th} sentence of the k_{th} article; W_j is a binary value. When the j_{th} tag belongs to both the set TR and S_e^k, then $W_j = 1$; otherwise $W_j = 0$.

In addition to the similarity between sentences and tags, we apply Latent Semantic Analysis (LSA) to compute an $n \times n$ sentence–sentence association matrix **S** (the entry denotes as $s_{g,h}$) to obtain the relation between sentences and the article; This process is similar to the paragraph analysis conducted previously. The value of diagonal elements c in the significance level of the eigenvector indicates the representativeness of specific sentence in the article. Finally, we compare the sentence score, which is

$$SC_e = c_e + W_e^k$$

where c_e is the representative score of e_{th} sentence; SC_e is the e_{th} sentence score—the sum of the sentence representative score and the tag score. It explains in the reader regarding what the article is about. Then after that it goes on to explain the subject or what the article is about. A sentence is better than another depending on the score, it means a higher score, and more persuasive is the sentence. Thus, the sentence with highest sentence score will be the key sentence of the paragraph.

A.6. Prior knowledge generation stage

After we identify the key sentence representing a paragraph, the query we used to find the prior knowledge article from the supplementary material database is combined with the key sentence and the entire paragraph. The query examines the prior knowledge database to find the most similar article to serve as a prior knowledge supplement for the paragraph. The search comparison method we use is shown below,

$$Sim\left(D, Q_i^k\right) = \sum_{j=1}^{m} W_j^{k,i'} \times W_j + \sum_{l=1}^{n} W_{L_l}$$

$$W_j = \begin{cases} 1, & T_j^{k,i} \in \text{the word of } D \\ 0, & T_j^{k,i} \notin \text{the word of } D \end{cases}, \quad W_{L_l} = \begin{cases} 1, & L_l \in \text{the word of } D \\ 0, & L_l \notin \text{the word of } D \end{cases}$$

where D is a prior knowledge article, Q_i^k is the query of the i_{th} paragraph in the k_{th} article, W_{L_l} is the same as W_j is a binary value, and L_l is the l_{th} word in Q_i^k. When the l_{th} word belongs to the word set of D, then $W_{L_l} = 1$; otherwise $W_{L_l} = 0$. When the j_{th} tag belong to the word set of D, then $W_j = 1$; otherwise $W_j = 0$. The more similar the prior knowledge article is to the query, the greater the value of $Sim(D, Q_i^k)$. The article with the highest value is then selected as the most suitable prior knowledge article for the student.

Appendix B. Questionnaire

1. I_1: Remind myself of meaningful ideas and memorize cues by article structure generation.

   Strongly disagree |_|_|_|_|_| Strongly agree

2. I_2: Understanding article structure helps me identify new information from articles more easily.

   Strongly disagree |_|_|_|_|_| Strongly agree

3. I_3: The presentation of the article structure is very intuitive and easy to understand.

   Strongly disagree |_|_|_|_|_| Strongly agree

4. I_4: The highlighted information provides me with a quick and useful personal snapshot of the reading material.

   Strongly disagree |_|_|_|_|_| Strongly agree

5. I_5: The network of prior knowledge, which provides the supplementary materials, can help me quickly constructing prior knowledge reservoir.

   Strongly disagree |_|_|_|_|_| Strongly agree

6. I_6: It is easier for me to expand prior knowledge of related topics in an article.

   Strongly disagree |_|_|_|_|_| Strongly agree

7. I_7: The network of prior knowledge can enhance my reading comprehension of relevant supplementary materials.

   Strongly disagree |_|_|_|_|_| Strongly agree

8. I_8: Exploiting prior knowledge clues provide me with inferring meaning and understanding unfamiliar vocabulary.

   Strongly disagree |_|_|_|_|_| Strongly agree

9. I_9: Exploiting tagging information provide me with effective feedback during the learning process.

   Strongly disagree |_|_|_|_|_| Strongly agree

10. I_{10}: The tagging activities inspire me to think new ideas who lost or has never been noticed.

    Strongly disagree |_|_|_|_|_| Strongly agree

11. I_{11}: Tagging activity can enhance summarize new ideas in reading process.

    Strongly disagree |_|_|_|_|_| Strongly agree

12. I_{12}: Review of previous you own tags can facilitate the recall of ideas and information in the story.

    Strongly disagree |_|_|_|_|_| Strongly agree

13. I_{13}: I think the tags with tagging object that easily grasp the structure and concepts of reading article.

    Strongly disagree |_|_|_|_|_| Strongly agree

14. I_{14}: Using tags enables the efficiency of reading.

    Strongly disagree |_|_|_|_|_| Strongly agree

15. I_{15}: I think that the process of reading given to tags is helpful for learning.

    Strongly disagree |_|_|_|_|_| Strongly agree

16. I_{16}: The ease of use of interface and its simple to understand

    Strongly disagree |_|_|_|_|_| Strongly agree

17. I_{17}: The process of TAK system has a clear vision.

    Strongly disagree |_|_|_|_|_| Strongly agree

18. I_{18}: I can get started quickly with the TAK system

    Strongly disagree |_|_|_|_|_| Strongly agree

19. I_{19}: I can understand feedback information in TAK system

    Strongly disagree |_|_|_|_|_| Strongly agree

20. I_{20}: The user interface is simple to learn and efficient to use

    Strongly disagree |_|_|_|_|_| Strongly agree.

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