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Applying social tagging to manage cognitive load in a Web 2.0 self-learning environment

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Web-based self-learning (WBSL) has received a lot of attention in recent years due to the vast amount of varied materials available in the Web 2.0 environment. However, this large amount of material also has resulted in a serious problem of cognitive overload that degrades the efficacy of learning. In this study, an information graphics method is proposed to resolve this problem. This method is based on social tagging, which is used to visualize the relationships among materials and can thus assist learners in facilitating learning. To examine the feasibility of the proposed method for managing cognitive load, an experimental model was designed in which cognitive load theory was adopted as the theoretical framework. A total of 60 university students participated in the experiment, and the partial least squares method was used to verify the experimental model. The results show that the information graphics method has a positive impact on three types of cognitive load, namely intrinsic, extraneous, and germane. Furthermore, intrinsic and germane cognitive load have a positive influence on perceived learning effectiveness, while extraneous cognitive load does not have a significant influence. One possible reason for this outcome is that the problem of visual load was not considered in the design of this study. The overall summary of the findings is that the use of social tagging can effectively manage cognitive load and positively links to perceived learning effectiveness.

Keywords: web-based self-learning; information graphics method; social tagging; cognitive load theory; partial least squares

1. Introduction

Web-based self-learning (WBSL) has been becoming increasingly popular due to the wide diversity of materials available online. The development of Web 2.0 provides an efficient platform for individuals to share and exchange experience and knowledge, is a key to this success (Churchill, 2009; Kerawalla, Minocha, Kirkup, & Conole, 2009; Kim, 2008). Consequently, learners can now selectively access a huge range of preferred learning materials through...
Internet (Burden & Parker, 2008; Fu, Wu, & Ho, 2009) and even engage themselves in self-learning in many circumstances.

Nevertheless, the dramatic growth in the amount of material has also brought about the problem of cognitive overload, which may lead to disorientation and significant learning difficulties (Mayer & Moreno, 2003; Sweller, van Merrienboer, & Simon, 1998). Thus, how to tackle the cognitive overload in Web 2.0 seems vital to the success of online learning, especially in a WBSL environment.

In this study, an information graphics method is proposed to solve the problem of cognitive overload in WBSL, through the approach transforming the verbal information among materials into a relationship map. Dual coding theory (Clark & Paivio, 1991) states that visual information is processed in both imagery and verbal cognitive systems, while verbal information is processed only in the verbal cognitive system. This means that the effects of visual information on learning are more significant than those of verbal information (Clark & Paivio, 1991; Schnitz, 2002). Moreover, previous research (Steinberg, 1989) indicated that the use of maps is a useful strategy to cope with cognitive overload. This is linked to the idea that maps can assist learners in navigating the materials (Lo, Wang, & Yeh, 2004), giving them a sense of control and thus reducing both disorientation and cognitive overload (Brusilovsky, 2004). By the inspiration, the social tagging of materials was employed in this study to construct the relationship map of materials to assist learners. Social tagging proposes that users can utilize keywords (i.e. verbal information) to categorize Internet resources (Trant, 2009), and these words are then used to produce a visual relationship map.

To better realize the potential effectiveness of the information graphics method in the WBSL environment, an experiment based on cognitive load theory (CLT) (Sweller et al., 1998) was conducted in this study. Specifically, we developed an information graphics method to construct the above relationship map of materials, being used subsequently to assist learners in managing cognitive load in WBSL.

2. Background and related studies

2.1. Social tagging and relevant research

Social tagging (also known as folksonomy) means that users employ tags (i.e. keywords or terms) to categorize Internet resources in the Web 2.0 environment (Trant, 2009; Vander Wal, 2005b). This practice is also known as collaborative tagging, social classification, and social indexing (Anila, 2008).

Social tagging can be divided into two classes: broad and narrow (Vander Wal, 2005a). Broad social tagging is defined as “many people tagging the same object and every person can tag the object with their own tags in their own vocabulary” (Vander Wal, 2005a), and this approach is utilized at del.icio.us. Narrow social tagging is defined as “done by one or a few people providing tags that the person uses to get back to that information” (Vander Wal, 2005a), such as on the photography site Flickr.

Due to the growing popularity of social tagging, many researchers have used the concept in managing nontext data. The relevant literatures include the topics of information retrieval (Levy & Sandler, 2009), and information recommendation (Symeonidis, Nanopoulos, & Manolopoulos, 2010), and a review of the related research can be found in Trant’s study (Trant, 2009). The consensus of those studies
comes to the idea that social tagging is a sound approach for managing resources in a Web 2.0 environment.

2.2. CLT and relevant research

CLT assumes that a learner’s working memory can be conceptualized as a cognitive system that is of limited capacity and thus can only consider a limited number of elements at the same time (Miller, 1956; Siegel & Ryan, 1989; Sweller et al., 1998). Moreover, some studies indicate that a learner’s performance is affected by whether the cognitive load of a task exceeds the limits of their working memory (DeStefano & LeFevre, 2007; Maxwell, Masters, & Eves, 2003). In other words, CLT focuses on the limits of the working memory in order to develop useful instructional designs that can enhance learning effectiveness (Sweller & Chandler, 1991).

The literature (Sweller et al., 1998) distinguishes three types of cognitive load: intrinsic, extraneous, and germane. Intrinsic cognitive load (ICL) is determined by the inherent nature of the materials and learners’ prior knowledge (Cierniak, Scheiter, & Gerjets, 2009; Madrid et al., 2009). It is generally accepted that ICL is affected only by the materials rather than the instructional design and is less easier to reduce than other types of cognitive load, although a number of studies have attempted to design ICL-alleviated materials (Cierniak et al., 2009; Kester, Kirschner, & van Merriënboer, 2006; Pollock, Chandler, & Sweller, 2002; van Merriënboer, Kirschner, & Kester, 2003). Extraneous cognitive load (ECL) is caused by an improper instructional design and has been proven as a detriment to learning (Cierniak et al., 2009; Kolfschoten et al., 2010). For example, in some materials, the text and image are physically separated, which introduce unnecessary information processing, since learners need to switch back and forth between the two kinds of media to fully comprehend them (Cierniak et al., 2009). Finally, germane cognitive load (GCL) is resulted by an appropriate instructional design and has been shown to be beneficial to learning (Cierniak et al., 2009). The concept behind GCL is that an appropriate instructional design can motivate learners to indulge themselves in the processing, construction, and automation of schemas and then store them in their long-term memory (Kolfschoten et al., 2010; Sweller et al., 1998).

To design a sound learning environment, our instructional design plainly aims at managing ICL, reducing ECL, and promoting GCL. To achieve the purpose, first, we attempt to visualize the relationships among materials by using a map, so that the relationships can be well organized in a controllable manner to reduce potential complexity for the first aim, managing ICL. Second, we reduce ECL by incorporating text information (i.e. descriptions of nodes) directly into the map. Third, we promote GCL by providing rich and diverse materials from different Web 2.0 repositories. Through the three phases above, the proposed method is expected create a better web-based learning environment in terms of cognitive load.

3. Information graphics method

In this section, we present the information graphics method. Figure 1 shows the basic idea of the information graphics method. The left part shows a situation where a
A learner searches for information without information graphics, and thus the results returned contain a lot of verbal information. This may cause a learner’s cognitive overload, exceeding the limits of his or her working memory, because the learner needs to clarify the relationships among overwhelming verbal information. To solve this problem, an information graphics method is proposed, as shown in the middle part of Figure 1. The information graphics method uses tags to visualize the verbal information, which is achieved by using extraction, preprocessing, and construction mechanisms. The extraction mechanism is used to extract the relevant data, including both materials and tags. The preprocessing mechanism cleans the tags to prevent from containing many synonyms. Finally, the construction mechanism analyzes the relationships between materials and tags and then produces the relationship map. Once the construction mechanism has been completed, the relationship map of the materials is output to the learner, as shown in the right part of Figure 1. The details of the information graphics method are presented as follows.

### 3.1. Extraction mechanism

The extraction mechanism extracts the materials and the tags according to a learner’s request. First, the learner can submit a keyword and then the system utilizes it to extract the materials from several external resources. Table 1 shows some of popular external resources of Web 2.0 applications. The second stage is to extract the tags of the materials. If some materials are without any tags, the title (i.e. the file name) associated with them will serve as the purpose instead. Once the materials and the tags have been extracted, the preprocessing mechanism will be activated to clean the raw tags.

<table>
<thead>
<tr>
<th>Name</th>
<th>Format</th>
<th>Link</th>
</tr>
</thead>
<tbody>
<tr>
<td>YouTube</td>
<td>Video</td>
<td><a href="http://www.youtube.com">www.youtube.com</a></td>
</tr>
<tr>
<td>SlideShare</td>
<td>Slides</td>
<td><a href="http://www.slideshare.net">www.slideshare.net</a></td>
</tr>
<tr>
<td>Flickr</td>
<td>Photos</td>
<td><a href="http://www.flickr.com">www.flickr.com</a></td>
</tr>
<tr>
<td>iJigg</td>
<td>Audio</td>
<td><a href="http://www.ijigg.com">www.ijigg.com</a></td>
</tr>
<tr>
<td>Google blog search</td>
<td>Text</td>
<td>blogsearch.google.com</td>
</tr>
</tbody>
</table>
3.2. Preprocessing mechanism

The preprocessing mechanism checks the tags one by one, since they may contain some meaningless or redundant information. This mechanism is composed of three stages, namely removal of stopwords, stemming, and checking synonyms. With respect to the removal of stopwords, a Chinese/English stopword list is used to filter meaningless words, such as “a”, “an,” and “the.” When the stopwords have been removed, the Porter Stemming Algorithm (Porter, 1980) is used to normalize the tags. This algorithm matches morphological word variants by using the base or root form, so that morphological variants of the same word can be distinguished more easily. For instance, “tagging” is stemmed to “tag.” In addition, this stage only deals with the English tags, because the Chinese ones do not have the problem of stemming. After normalization, the next stage will deal with the issue of synonyms. The Sinica BOW (Bilingual Ontological Wordnet) is used to distinguish the synonyms, because it contains a large lexical database of Chinese/English terms in which synonyms are grouped into sets (Huang, 2003). Consequently, meaningless or redundant tags can be filtered out through the preprocessing mechanism.

3.3. Construction mechanism

The construction mechanism is used to produce the relationship map of the materials. This mechanism comprises two stages, namely tag selection and relationship analysis. The tag selection stage selects a subset of relevant tags, since not all the tags are meaningful in representing the material itself. In this stage, the $tf$-$idf$ (term frequency-inverse document frequency) technique is used to select the relevant tags (Manning, Raghavan, & Schütze, 2008; Salton & McGill, 1983), and it can estimate how significant a particular term is in a collection of documents, based on the number of times a term occurs in a given material (i.e. $tf$), offset by the frequency of the term in the collection space (i.e. $idf$) (Manning et al., 2008). Consequently, this technique can be used to select the relevant tags, and a detailed description is given in Appendix 1.

The relationship analysis stage examines the relationships among the materials and tags and further visualizes the overall structure in order to make it more comprehensible. Here, the formal concept analysis (FCA) method, a mathematical technique for categorizing binary relations (Ganter & Wille, 1999) into either \{objects and attributes\} or \{documents and terms\} (Priss, 2006), is adopted for the stage. In this study, the materials and the tags are used as the binary relations. To implement FCA, the Concept Explorer tool (Concept Explorer, 2009) is utilized because of its user-friendly interface. Consequently, the conceptual structures among materials can be identified and visualized through FCA, a detailed example is given in Appendix 2.

4. Design of experiment

To examine the effects of our proposed method on self-learning, an experimental model is proposed based on CLT, as shown in Figure 2. In this model, an independent variable (characteristics of the material) was manipulated and two dependent constructs were measured (cognitive load and perceived learning
effectiveness). Here, the proposed method is used to visualize the relationships among materials to the map, so that the characteristics of the material are selected as the independent variable. Besides, previous studies (Brusilovsky, 2004; Lo et al., 2004) indicated that the map is helpful to reduce cognitive load and promote learning effectiveness. Accordingly, cognitive load and perceived learning effectiveness were selected as the dependent constructs, in which cognitive load is applied to mediate the relationship between the characteristics of the material and perceived learning effectiveness (Cierniak et al., 2009; Homer, Plass, & Blake, 2008). The model contains six hypotheses, which are described below.

In the three types of cognitive load, ICL is influenced very slightly by instructional design alone, because that ICL is determined by the interactivity between the materials. However, some strategies have been developed to reduce ICL, such as isolated-interacting elements (Pollock et al., 2002), simple-to-complex sequencing of learning tasks (van Merriënboer et al., 2003), and just-in-time information presentation (Kester et al., 2006). The common purpose of all these strategies is that they aim to help learners reduce working memory so as to facilitate learning. In this study, by visualizing the relationships among the materials, the working memory can be reduced from handling intricate relationships among materials for learners. Therefore, the first hypothesis is as follows:

**H1.** Visualization of the relationships among materials will reduce ICL.

Appropriate instructional materials, such as with integrated and related text and images, should reduce ECL, because unnecessary cognitive processes can be avoided. Previous studies indicated that once text and images are physically separated, ECL will increase (Cierniak et al., 2009; Kolfschoten et al., 2010). In this work, the information in the relationship map of materials is spatially integrated, and thus the second hypothesis is proposed, as follows:

**H2.** Integration of the information contained in the materials will reduce ECL.

In contrast to ICL and ECL, GCL is beneficial to learning with the proper instructional design to increase the attention of individuals, so that they are able to more concentrate on learning (Kolfschoten et al., 2010; Sweller et al., 1998). Recent research found that students immerse themselves in learning if they are exposed to a rich multimedia experience (Fallahkhair, Pemberton, & Griffiths, 2005; Liu, Liao, & Pratt, 2009). Consequently, multimedia materials, containing video, images, audio,
H3. Increased diversity in the presentation of materials will promote GCL.

According to research on CLT (Cierniak et al., 2009; Kolfschoten et al., 2010; Madrid et al., 2009; Sweller et al., 1998), ICL and ECL are negative to learning performance, while GCL is beneficial to it. In this research, we try to reduce ICL and ECL and promote GCL and further to influence perceived learning effectiveness, which is defined as learners’ judgments of their capabilities to attain designated competence of performance (Chou & Liu, 2005; Epstein & Hundert, 2002). Consequently, the fourth, fifth, and sixth hypotheses are plainly stated as follows:

H4. Reduction of ICL will increase perceived learning effectiveness.
H5. Reduction of ECL will increase perceived learning effectiveness.
H6. Promotion of GCL will increase perceived learning effectiveness.

4.1. Participants

The participants were from one class of a university in Tainan City, Taiwan, and their average age was 20 years (SD = 1.08). All of the participants are with the Department of Network Multimedia Design, and a total of 60 students enrolled in the experiment and participated in the project over the course of one semester.

4.2. Procedure

The experimental procedure is shown in Figure 3 and is composed of four stages: (i) regular project course, (ii) self-learning activity, (iii) project presentation, and (iv) questionnaire. In the first stage, the instructor introduced the lessons and then each student carried out their project. In the second stage, a self-learning activity was used to enhance the presentation skills of students, and before this, some training was given. After the training, the participants were asked to perform a self-learning activity by using the system. In the third stage, the students presented their own project in a public forum. In the final stage, once the project presentation activity was completed, the students were asked to fill out a questionnaire in testing the proposed experimental model.

<table>
<thead>
<tr>
<th>id</th>
<th>activity</th>
<th>duration</th>
<th>schedule</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>regular project course</td>
<td>15w</td>
<td>1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18</td>
</tr>
<tr>
<td>2</td>
<td>self-learning activity</td>
<td>2w</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>project presentation</td>
<td>2w</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>questionnaire</td>
<td>1w</td>
<td></td>
</tr>
</tbody>
</table>

Figure 3: Procedure of the experiment.
4.3. Measurements

The questionnaire was developed based on the experimental model and prior research (Cierniak et al., 2009; Epstein & Hundert, 2002), as well as feedback from 10 participants and 2 experts. The questionnaire involves three constructs: the characteristics of the material, cognitive load, and perceived learning effectiveness. The construct of characteristics of the material was developed by this study and used to investigate students’ perception of the material. The material comprises three characteristics: the visualization of the relationships among materials, integration of the information contained in the materials, and increased diversity in the presentation of materials. The construct of cognitive load was modified from the Cierniak et al.’s study (2009), which was used to investigate students’ perception of the cognitive load, that is, ICL, ECL, and GCL. The construct of perceived learning effectiveness was developed by referring to two previous study (Epstein & Hundert, 2002; Huang & Liu, 2009), which was used to investigate students’ perception of the learning effectiveness. Table 2 shows the final questionnaire that was distributed to the students, who were asked to indicate their level of agreement with a number of statements on a 5-point Likert scale.

4.4. Materials

The focus of the self-learning activity was improving presentation skills, and the materials were obtained from some of the common Web 2.0 websites. The materials

<table>
<thead>
<tr>
<th>Table 2. Questionnaire.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visualization of relationships</td>
</tr>
<tr>
<td>(VR1) I can easily understand the relationships among the materials.</td>
</tr>
<tr>
<td>(VR2) I can easily choose the material that I want to study.</td>
</tr>
<tr>
<td>Integration of information</td>
</tr>
<tr>
<td>(II1) I can easily see that each node corresponds to the properties in the map.</td>
</tr>
<tr>
<td>(II2) I can easily see that each node corresponds to the materials in the map.</td>
</tr>
<tr>
<td>Diversity of presentation</td>
</tr>
<tr>
<td>(DP1) The learning system can provide a variety of materials.</td>
</tr>
<tr>
<td>(DP2) The learning system can provide knowledge of different types of the materials.</td>
</tr>
<tr>
<td>ICL</td>
</tr>
<tr>
<td>(ICL1) This topic is easy to learn.</td>
</tr>
<tr>
<td>(ICL2) This topic does not require a lot of mental effort.</td>
</tr>
<tr>
<td>ECL</td>
</tr>
<tr>
<td>(ECL1) Utilizing the materials to learn is easy.</td>
</tr>
<tr>
<td>(ECL2) Utilizing the materials to learn does not require a lot of mental effort.</td>
</tr>
<tr>
<td>GCL</td>
</tr>
<tr>
<td>(GCL1) My attention is concentrated on the self-learning activity.</td>
</tr>
<tr>
<td>(GCL2) My mood is joyful during the self-learning activity.</td>
</tr>
<tr>
<td>Perceived learning effectiveness</td>
</tr>
<tr>
<td>(PLE 1) I believe I can apply the knowledge from the learning system to real-world situations.</td>
</tr>
<tr>
<td>(PLE 2) I believe I can enhance my presentation skills via this learning system.</td>
</tr>
</tbody>
</table>

Note: VR, visualization of relationships; II, integration of information; DP, diversity of presentation; PLE, perceived learning effectiveness.
were selected by the instructor, because this activity was a significant challenge for learners. Figure 4 shows the relationship map of materials based on the information graphics method, which students utilized in the self-learning activity. Figure 5 shows the students taking part in the self-learning activity by using the relationship map of materials.

Figure 4. The self-learning materials mapped by the information graphics method.

Figure 5. The students using the relationship map of materials to take part in the self-learning activity.
5. Results and discussion

In this study, the partial least squares (PLS) method is used to verify the experimental model (Chin, Marcolin, & Newsted, 2003). PLS is a novel path analysis method, which is used as an alternative to ordinary least squares regression or structural equation modeling. Unlike traditional path analysis methods, PLS is capable of treating a small sample (minimum sample size \(n \geq 20\)) (Chin & Newsted, 1999). In this paper, SmartPLS 2.0 was used to assess the measurement and structural models (Ringle, Wende, & Will, 2005).

5.1. Measurement model

The measurement model was assessed by convergent validity, reliability of measures, and discriminant validity. The convergent validity uses the average variance extracted (AVE), in which the AVE must exceed the standard minimum level of 0.5 (Hair, Black, Babin, Anderson, & Tatham, 2006). The reliability of the measurement model is examined using the composite reliability and Cronbach’s \(\alpha\). In general, the minimum value of composite reliability is 0.7, and the minimum value of Cronbach’s \(\alpha\) is 0.6 (Hair et al., 2006; Nunnally, 1978). To evaluate the discriminant validity, the square roots of AVEs are compared to the correlations among the latent variables (Fornell & Larcker, 1981), in which all latent correlations are less than the corresponding AVE square roots. Table 3 shows the results of the measurement model with an acceptable quality, since all the values meet the standard level.

5.2. Structural model

The structural model is used to test the hypothesized paths, using path coefficients (\(\gamma\) and \(\beta\)), \(R^2\) value, and bootstrapping (500 resamples) (Nijssen & Herk, 2009). The results of the structural model are summarized in Table 4, which shows the results for the six hypotheses. The results show that the model can illustrate 39% of the variation in ICL, 25% of the variation in ECL, 41% of the variation in GCL, and 58% of the variation in perceived learning effectiveness. However, there is one hypothesis not being supported, namely H5, followed by H6 that was also supported.

Table 3. Summary of measurement model.

<table>
<thead>
<tr>
<th></th>
<th>Convergent validity AVE</th>
<th>Reliability of measures Composite reliability</th>
<th>Cronbach’s (\alpha)</th>
<th>VR</th>
<th>II</th>
<th>DP</th>
<th>ICL</th>
<th>ECL</th>
<th>GCL</th>
<th>PLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>VR</td>
<td>0.89</td>
<td>0.94</td>
<td>0.88</td>
<td>0.94</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>0.91</td>
<td>0.95</td>
<td>0.90</td>
<td>0.77</td>
<td>0.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>0.92</td>
<td>0.96</td>
<td>0.92</td>
<td>0.67</td>
<td>0.71</td>
<td>0.95</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICL</td>
<td>0.80</td>
<td>0.89</td>
<td>0.76</td>
<td>0.62</td>
<td>0.62</td>
<td>0.59</td>
<td>0.89</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECL</td>
<td>0.89</td>
<td>0.94</td>
<td>0.88</td>
<td>0.43</td>
<td>0.50</td>
<td>0.40</td>
<td>0.76</td>
<td>0.94</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GCL</td>
<td>0.72</td>
<td>0.84</td>
<td>0.62</td>
<td>0.59</td>
<td>0.67</td>
<td>0.64</td>
<td>0.71</td>
<td>0.58</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>PLE</td>
<td>0.79</td>
<td>0.88</td>
<td>0.73</td>
<td>0.65</td>
<td>0.71</td>
<td>0.77</td>
<td>0.66</td>
<td>0.55</td>
<td>0.73</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Note: VR, visualization of relationships; II, integration of information; DP, diversity of presentation; PLE, perceived learning effectiveness.
like H1–H4. In short, most of the expected effects were strongly confirmed, and these results are given in Figure 6.

5.3. Discussion

H5, was that ECL did not have a significant effect on perceived learning effectiveness. One reason for rejecting H5 is that although the text and images were integrated in the material, the problem of visual load was still not considered. The visual load is a possible problem in information visualization (Assa, Cohen-Or, & Milo, 1997), and the assumption is that an acceptable diagram should not include an excessive amount of information (Assa et al., 1997). In this study, the information signifies the materials, the tags, and the relationships among them. Hence, if the number of materials and tags is continuously increasing, the relationship map will obviously become more complicated. In other words, learners will find it difficult to discover relevant material from a large pool of information (Yang, Chen, & Hong, 2003). To overcome this problem, a useful technique is zooming in/out, which is a common approach in geographic information systems.

Table 4. Summary of structural model.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Independent variable</th>
<th>Dependent variable</th>
<th>( \gamma )</th>
<th>( \beta )</th>
<th>( t )</th>
<th>( p )</th>
<th>Result</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>VR</td>
<td>ICL</td>
<td>0.62</td>
<td>10.11</td>
<td>0.00*</td>
<td></td>
<td>Supported</td>
<td>0.39</td>
</tr>
<tr>
<td>H2</td>
<td>II</td>
<td>ECL</td>
<td>0.50</td>
<td>5.00</td>
<td>0.00*</td>
<td></td>
<td>Supported</td>
<td>0.25</td>
</tr>
<tr>
<td>H3</td>
<td>DP</td>
<td>GCL</td>
<td>0.64</td>
<td>8.16</td>
<td>0.00*</td>
<td></td>
<td>Supported</td>
<td>0.41</td>
</tr>
<tr>
<td>H4</td>
<td>ICL</td>
<td>PLE</td>
<td>0.23</td>
<td>2.55</td>
<td>0.01*</td>
<td></td>
<td>Supported</td>
<td>0.58</td>
</tr>
<tr>
<td>H5</td>
<td>ECL</td>
<td></td>
<td>0.06</td>
<td>0.44</td>
<td>0.66</td>
<td></td>
<td>Rejected</td>
<td></td>
</tr>
<tr>
<td>H6</td>
<td>GCL</td>
<td></td>
<td>0.53</td>
<td>5.51</td>
<td>0.00*</td>
<td></td>
<td>Supported</td>
<td></td>
</tr>
</tbody>
</table>

Note: VR, visualization of relationships; II, integration of information; DP, diversity of presentation; PLE, perceived learning effectiveness; \( ^* \)p < 0.05.

Figure 6. Structural model. 
Lo, Chang, Tu, & Yeh (2009). This method means that users can zoom into a part of the diagram to observe the local details or zoom out of it to observe the global view (Yang et al., 2003). In future work, we will study this technique to see how effective it is in alleviating the visual load associated with more complicated relationship maps.

Although the hypotheses were not fully confirmed, the value of the proposed method in WBSL cannot be neglected, especially in Web 2.0 context. In contemporary age of Internet, learners frequently used search engine to seek various learning materials for pursuing knowledge. However, learners may encounter certain difficulties regarding how to organize these materials. In the situation, our proposed method provides a promising means for assisting learners in organizing these materials through visualizing the relationship among them. In this manner, learners can easily understand the relationship among these materials and further reduce their cognitive load. Nevertheless, the proposed method still has room for improvement when it is used in real-world applications. In this current study, the proposed method can only assist learners in visualizing the relationship among these materials but cannot assist learners in selecting appropriate materials from the mass of materials. More specifically, the problem of adaptive learning is not addressed in this study. Adaptive learning means that the materials are dynamically adjusted to suit the needs or different levels of learners. Accordingly, adaptive learning needs to be developed and implemented in further work when the proposed method is used in the real-world educational context.

6. Conclusions

Our research applied social tagging to manage the three types of cognitive load in a WBSL environment. To reduce ICL, we proposed an information graphics method to visualize the relationships among materials. Then to reduce ECL, we integrated text information (i.e. the description of nodes) directly into the image (i.e. the relationship map of materials). Finally, to promote GCL, rich and varied materials were provided for learners. By employing this instructional design, we expect that learners can achieve improved perceived learning effectiveness.

To explore the potential of the proposed information graphics method, CLT was applied to design the experimental model and to examine which factors may influence students’ perceived learning effectiveness. To avoid the effect of the small sample sizes, the PLS method was used to examine the hypotheses, which were all but H5 confirmed. The invalid hypothesis, H5, is that the reduction of ECL did not have a positive impact on perceived learning effectiveness. One of the reasons for the rejection is that the problem of visual load was not considered, and thus, in future work, we aim to apply the zooming in/out technique to address this issue.

Although the proposed method has demonstrated its benefits, some problems remain and should be addressed in future research. One major problem is how to select appropriate materials from the vast Web 2.0 repository. Accordingly, in future work, we will design an approach to select the appropriate materials to meet the needs of learners with different proficiency levels. Limitations of this study include the type of the measurements and the relatively small sample size. In this study, all of the measurements are limited in the students’ current self-reported perceptions. In the future work, we will introduce additional measurements to explore the
relationship between cognitive load and learning effectiveness. Furthermore, increasing sample size to obtain a stronger evidence for the proposed information graphics method will be expected as well.

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References


Appendix 1

This appendix describes how to use the tf-idf technique to select the relevant tags in this study. The tf signifies the frequency of a given tag in a given material. In other words, a large tf means that the tag is more important. As a result, the formula for tf can be defined as in Equation (1).

\[ tf_i(m_j) = \frac{\text{freq}_i(m_j)}{\sum_{i=1}^{k} \text{freq}_i(m_j)} \]  

where \( \text{freq}_i(m_j) \) is the frequency of occurrence of the tag \( t_i \) in the material \( m_j \), and \( \sum_{i=1}^{k} \text{freq}_i(m_j) \) is the frequency of occurrence of all tags in the material \( m_j \).

The idf represents the frequency of documents containing the given tag in a given collection space, and thus a large idf means that the tag occurs frequently in many documents. This means that the tag is not a good discriminator and should be given less importance (Robertson, 2004). As a result, the formula for idf can be defined as in Equation (2).

\[ \text{idf}_i = \log \frac{|D|}{|\{d : t_i \in d\}|} \]  

where \( |D| \) is the total number of documents in the collection space, and \( |\{d : t_i \in d\}| \) is the number of documents containing the tag \( t_i \).

After the formulation of tf and idf, the importance of each tag can be evaluated through Equations (1) and (2). Thus the importance of each tag is defined as in Equation (3).

\[ w(t_i(m_j)) = tf_i(m_j) \times \text{idf}_i \]  

where \( w(t_i(m_j)) \) is the importance of tag \( t_i \) in the material \( m_j \).

Subsequently, the significant tags can be selected by comparing their importance.

Appendix 2

This appendix uses an example to describe how to use FCA to construct the relationship map of materials.

Figures A1 and A2 show an example of FCA. Figure A1 shows an example of a formal context, represented by an asterisk table, which is composed of a set of materials, a set of tags, and a relation description in which one material has been tagged by one tag represented by an asterisk.

Figure A2 shows an example of a concept lattice. This diagram changes from a formal context (e.g. Figure A1 in this example) to a line diagram of a concept lattice. The concept
lattice is composed of a set of formal concepts of a formal context and the subconcept–superconcept relations between these (Jiang, Pathak, & Chute, 2009; Priss, 2006). In the concept lattice, a formal concept is represented as a node. Each node connects to a set of materials, and this is called the extension, and each node connects to a set of tags, and this is called the intension. That is to say, the extension is composed of all the materials related to this node and its child nodes, and the intension involves all tags related to this node and its parent nodes. For example, the extension of \( c_1 \) is the \( m_1, m_2, \) and \( m_3 \), while the intension of \( c_2 \) is the \( t_1 \), and \( t_4 \). The subconcept is that the set of materials of one node is a subset of materials of another node, or the set of tags of one node is a superset of tags of another node, while the definition of superconcept is the opposite of that of subconcept. For instance, \( c_2 \) is a subconcept of \( c_1 \). Therefore, the relationships between materials and tags can be visualized as a line diagram through the twin concepts of subconcept and superconcept.

Figure A2. An example of the concept lattice for the formal context in Figure A1.