What Matters in Concept Mapping? Maps Learners Create or How They Create Them

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Abstract. Generative strategies, where learners process the target content while connecting different concepts to build a knowledge network, has shown potential to improve student learning outcomes. While concept maps in particular have been linked to the development of generative strategies, few studies have explored structuring the concept mapping process to support generative strategies, and few studies offer intelligent support. In this work, we present a concept mapping tool that offers navigational support in the form of hyperlinks, where nodes in the concept map are linked to segments of text. We evaluate the effect of the hyperlinks on generative strategies and learning outcomes through a week-long high school study with 32 participants. Our results indicate that proper navigational and visual aid during concept mapping facilitates the development of generative strategies, with implications for learning outcomes. Based on these findings, we propose a constraint-based tutoring system to adaptively support the development of generative strategies in concept mapping.

Keywords: concept map, generative strategies, constraint based model

1 Introduction

Diagrams and mapping tools have been used to improve learning by providing a visual display of information, concepts, and relations between ideas [1] [2]. One such tool is a concept map, which is a graphical representation that illustrates knowledge structures as labelled links (denoting relationships) between various labelled nodes (denoting specific concepts in the knowledge domain) [3]. Although concept maps have been reported to facilitate learning [18], the use of concept maps also comes with drawbacks. The main disadvantage of using concept maps is the complexity of the task and the training required [4]. While previous research has shown the benefits of providing feedback and scaffolding during concept mapping [5], many studies have focused on the quality of the completed map rather than evaluating the process by which it was made. For example, Hirashima assessed the quality of student-generated concept maps by using keyword matching to compare the nodes in the concept map with keywords from the learning content [6]. Others have developed systems to provide immediate feedback [e.g., 7], but these still focus on the product students create rather than intelligently monitoring the cognitive process.

We argue that it is just as important to consider how the concept maps are created when considering possible forms of intelligent support. For example, in what order are the concept nodes and links created? How much are students comparing concepts while constructing the map? Even two identical maps can result from two completely different strategies, and these strategies might influence learning results. Among different types of learning strategies, generative strategies have shown to have powerful impact on student learning. Generative strategies refer to behaviors and activities that involve the creation of relationships and knowledge networks among different concepts [8]. Research has demonstrated that generative strategies during reading, where learners process the learning content while comparing and connecting different concepts, lead to better learning outcomes than a linear strategy [9]. In addition, prior work suggests that concept mapping can be used as a valuable tool to develop generative strategies [15]. Supporting students in pursuing generative strategies during concept mapping may be highly beneficial.

In this paper, we present our design of a concept mapping environment that is integrated with a digital textbook. The environment is designed to scaffold generative strategies by allowing students to create concept maps directly from the textbook and then use them to navigate to relevant textbook content using a **hyperlink feature**. We hereby propose three hypotheses:

H_1: The hyperlink feature improves learning.
H_2: The hyperlink feature facilitates generative strategies.
H_3: The use of generative strategies predicts learning outcomes.

We investigate our hypotheses through a classroom study with 32 high school students. We discuss the implications of the study findings for developing a system that uses intelligent tutoring to promote generative strategies during concept mapping.

2 Related Work

The introduction of personal computers enabled the development of computer-based concept mapping tools such as CmapTools, Mindmaple, Mind Mapping and Mind Vector. Some of these tools, like CmapTools, have been extensively studied by researchers, and have demonstrated significant advantages over traditional concept mapping tasks [10]. These tools tend to provide features like fast input, easy modification, and map sharing, but do not fully utilize the interactive and intelligent potential of digital platforms to support students.

One way researchers have attempted to use digital technologies to scaffold beneficial learning strategies is by providing concept map based navigation, where students can click on a node in the concept map to navigate to the corresponding page, as opposed to reading the text in a fixed linear order. However, prior research on concept map based navigation failed to demonstrate positive impacts on learning gains [11] [12]. One explanation might be the maps given to student in the above studies are ready-made. Learners confronted with these ready-made maps may initially feel overwhelmed or demotivated by the complexity of the map [13], and thus, the benefits of quick access to relevant content are likely to be diminished by the cognitive load to process ready-made maps. In our work, students use concept maps that they created to navigate to relevant content, reducing the cognitive load of processing an unfamiliar map structure.

Another way researchers have used digital technologies in concept mapping is through the use of artificial intelligence. For instance, Weinbrenner and colleagues designed a system that provides feedback to students by comparing their concept maps with a domain ontology through keyword matching [19]. Similarly, Wu [7] presented a concept mapping environment that provides feedback based on the similarity between a student map and an expert map. These studies highlight the use of feedback in concept mapping, but the feedback given to students is mainly tailored to their final product, that is, the concept maps created by students. Few evaluate the process of constructing the maps. Mayer's work, which directly measured learners' cognitive processing during reading, revealed the importance of different strategies on learning outcomes [9]. In this present work, we evaluate the use of scaffolding to support generative strategies during concept mapping, with the eventual goal of developing adaptive feedback on concept mapping strategies.

3 System Design

In this work, we present an iPad-based interactive concept mapping tool that is integrated with a digital textbook. The tool enables students to create concept maps directly from the textbook content and, in turn, use the created map to access and navigate the content. The system was written in Objective-C, and the content displayed in the book is in .epub format to facilitate importing new materials as necessary. Our system is designed to support students in developing generative strategies during the concept mapping process. The following are the key features of the system:

1. Integrated text and concept map view. Our system has both a textbook view and a concept map view. When students hold the tablet in portrait mode, the system works as a traditional digital textbook. However, when the tablet is in landscape mode, the screen splits into two, with the left side displaying the textbook view and the right side showing the concept map view (see Figure 1). The dual-window alignment provides quick access to both views for easy comparison between the text and the concept map. The students navigate within the textbook view by swiping right to go forward and left to go back. Since the iPad screen is relatively small, especially when divided in half, we provide students with a concept map preview which indicates where students are within the overall concept map.

2. Concept map construction. To create the concept map, students can add a concept node by long pressing on the word or words in the textbook. This "click-to-add" feature is designed to ameliorate the extraneous effort of typing the concept name on the iPad, while encouraging the cognitively beneficial process of building the knowledge structure. If students want to customize their concept maps by creating nodes that do not come directly from the text, they can add concept nodes by clicking on the "+" icon in the concept map view and using the iPad keyboard to label their nodes. To link concepts, student first long press on a concept node, choose the linking option, and then tap the second node they want to link. Students can then choose a word from a suggested list or type their own word to specify the relationship between the two concepts. Students can delete concepts or the whole map as necessary.

3. *Concept map navigation*. When a concept is added to the textbook, it is hyperlinked to the page in the textbook that was active when it was created. To navigate back to that page, the student can click on the concept. In addition, if the student is navigating using the textbook view (swiping left or right), when the student arrives on a page, the concepts that were created on that page will be highlighted both in the concept map view and in the textbook view. We expect that this hyperlink navigation feature would better support students in pursuing generative strategies by helping them to compare concepts from different segments of text.

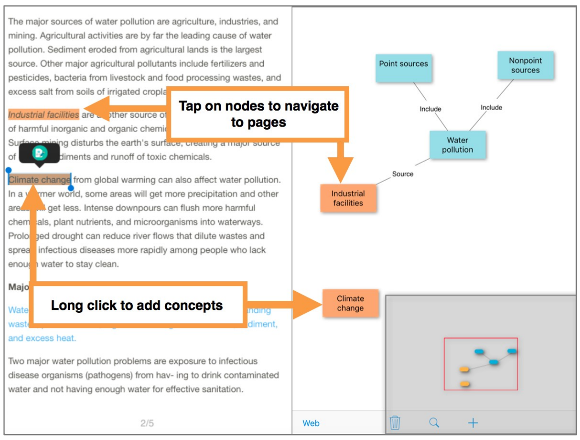

Fig. 1. Our application integrates a concept mapping tool with a textbook. Students can create concept maps directly from the textbook and use the created maps for navigation.

An example of generative strategies in the use of this application would be as follows. A student, Sam, reads the textbook and finds the concept "seed" on page 5. He uses the "click-to-add" feature to add a node named "seed" to the concept map view on the right. He continues to read the textbook. On page 30, where it talks about water pollution, he creates a node "water quality". Sam then realizes water quality might have something to do with the growth of the seed. He taps on the concept map node "seed" and the system navigates back to page 5. He finds that the growth of seeds largely depends on the oxygen level and mineral composition of underground water. He then taps on the node "water quality" and, jumping back to page 30, he finds that the water quality would affect the oxygen level and mineral composition. With this information, he links the concept map nodes "seed" and "water quality" and names the relationship as "depends on". From the example shown above, the hyperlink navigation feature adds flexibility to the fixed linear textbook structure and enables students to access key information located in different pages of the textbook. These comparisons are critical in developing generative strategies.

4 Study of Hyperlink Feature

We conducted a study to test whether our digital textbook application improves learning (H_1), improves the use of generative strategies (H_2), and whether the generative strategies are related to learning (H_3). We worked with a high school teacher who typically uses concept mapping activities in her classes. In this study, our digital textbook application is used as a substitute to the paper-and-pencil based tools typically used for the concept mapping activity. During the study, students read a textbook chapter and, over the course of 5 classroom periods, constructed a concept map to represent the knowledge structure of the chapter. We investigated students' interactions with the system and their corresponding learning outcomes.

4.1 Method

We recruited 32 participants from a high school 12th grade earth sciences class. All participants had previous experience with concept maps. The application was installed on an iPad 2 Air, with a 9.7-inch display and a multi-touch interface. The learning material consisted of a chapter from the 15th edition of *Living in the Environment: Principles, Connections, and Solutions*, the textbook that was being used in the class. The textbook displayed in the application was manually edited by us to fit the screen of the iPad. The original chapter had 27 pages and the iPad version had 58 pages.

Students were assigned to two conditions (hyperlink and non-hyperlink) via a randomized block design to control for pretest score. All students worked individually and kept his or her iPad for the duration of the study. Students in the hyperlink condition used the system described above. They were able to create concept maps from the book and tap on the nodes to navigate to the related pages, with relevant words in the textbook and concept map nodes highlighted. Students in the non-hyperlink condition used the same system, but with no hyperlink navigation or highlighting on words and concept map nodes.

Students began the study with a pretest, which was taken on a Thursday. The intervention, in which students used our application, began the following week on a Monday, and lasted 20 minutes per day for 5 consecutive days. On the first day, all of the participants were given a 10-minute in-app training session (tailored to condition) where they learned about how to use the application features through a step-based tutorial. Our intervention was integrated into normal classroom practice and was part of the broader unit on earth sciences taught by the teacher. Therefore, each day after using our system to create their concept maps, students received a related lesson from their teacher and continued to engage with related content on Monday and Tuesday the following week. Similarly, if students finished creating their concept map before the end of the fifth day, they worked on related content the teacher had prepared (e.g., an online reading task). The posttest was given on the Wednesday after the study was completed. During the study, all students' actions were logged and the final concept maps were uploaded to a server for analysis.

4.2 Measures

Learning. The pretest consisted of 30 multiple choice questions covering the whole chapter, and was designed by the high school teacher. The posttest consisted of the same questions as the pretest but in a different order. This was in accordance with the common practice of the classroom teacher, who constructed similar pre and posttests for every unit she taught. Learning results are measured by normalized gains [21].

Generative strategies. We model generative strategies using three variables.

1. *Back navigation*. A back navigation is the count of times a student navigates back a previous page after reading forward in the text. Several "back" actions in a row are counted as a single back navigation, but once the learner moves forward again, the next time they go back, a new back navigation will be counted. This captures when learners make comparisons between current concepts and previously recalled ones.
2. *Cross links.* We computed the number of cross links by counting the times two concept nodes that are created from two different pages are linked. This measure reveals that learners are establishing relationships among concepts located on different pages of the textbook. The higher number of cross links a student has, the more comparisons the student is making.
3. *Context switch.* Our log file records whether a student is interacting with the textbook view or the concept map view, so we are able to model how many times students' attention switches from the textbook view to the concept map view. A high number of context switches from a student is an indication that the student is frequently referring to the textbook and comparing it with the concept map while constructing it, which indicates generative strategies.

Using the above three variables, we computed an overall generative score that quantifies generative strategies as a whole by: 1) using *min–max* normalization [22] to rescale the three variables into [0, 1], and 2) averaging the three rescaled values to get an overall generative score, also between 0 and 1.

Concept map properties. We also computed three basic properties of the students' concept maps themselves:

1. *Total node.* The total number of concept nodes in the concept map.
2. *Total link*. The total number of links in the concept map.

3. *Link/node ratio.* Link/node ratio is computed as the number of concept links over the number of concept nodes in a given map. The link/node ratio indicates the overall connectivity of a concept map. The higher the link/node ratio is, the more connected a concept map is.

Student activities. Finally, we computed three variables from the log data that reflected student activity within the application.

1. Total actions. Total action is the total number of actions for each student.
2. Navigation actions. Navigation actions include turning pages and using hyperlink for navigation.
3. Hyperlink navigation actions. A hyperlink action is when a student clicks on a hyperlinked concept map node for navigation.

4.3 Results

Overview of Student Activity. In this section, we first present an overview of how students used our system to create concept maps for learning. As discussed in the method, not all students engaged in concept mapping for all study days, either due to being absent or completing the activity early. The actual attendance days are not significantly different between conditions, $F(1, 28) = 1.579$, $p = 0.219$. 23 students attended for 5 days (11 in the hyperlink condition, 12 in the non-hyperlink condition) and 7 students attended for 4 days (4 in the hyperlink condition, 3 in the non-hyperlink condition). Students who attended 5 days performed marginally less total actions than those who attended 4 days (p = 0.063). Two students (one in each condition) who attended less than 3 days are excluded from analysis.

Next, we looked at the basic properties of the concept maps that students produced (see Table 1). Overall, students created a mean of 40.90 nodes (SD = 19.75) and a mean of 37.80 links (SD = 19.14). We conducted a MANOVA with condition as the independent variable and number of concept nodes, number of concept links, and link/node as dependent variables. There was no significant difference between condition on the overall model ($F(3, 25) = 0.303$, $p = 0.823$, Wilks' $\lambda = 0.965$, partial $\eta^2 = 0.035$), and no significant effects of condition on the individual dependent variables.

Condition	#Concept Nodes		#Concept Links		#Link Over Node	
	Mean	SD	Mean	SD	Mean	SD
Hyperlink	42.42	18.91	38.40	19.48	0.91	0.16
Non-Hyperlink	39.60	21.15	37.20	19.45	0.93	0.11

Table 1. Variables for modeling concept map outcomes

As a proxy for student engagement, we examined whether student activity varied across conditions. We first examined whether the hyperlink feature influenced the total navigation and total actions. A one-way ANOVA revealed that there was no significant difference between condition on total actions performed ($F(1, 28) = 2.081$, $p = 0.160$), with the hyperlink condition having a mean of 371.80 actions ($SD = 108.55$) and the non-hyperlink condition having a mean of 452.93 actions ($SD = 188.83$). Similarly, there was no difference in number of navigation actions ($F(1, 28) = 2.705$, $p = 0.111$), with the hyperlink condition conducting on average 191.53 actions ($SD = 82.79$) and non-hyperlink conducting 276.33 actions ($SD = 181.74$). Students used the hyperlink navigation action a mean of 23.25 times, which is 12.14% of the total navigation actions taken.

H1: The hyperlink feature improves learning. Our hypothesis when designing the hyperlink feature was that the use of the hyperlink feature facilitates students in making connections between concepts, and thus, improves learning. To evaluate this hypothesis, we conducted a two-way repeated-measures ANOVA with condition as a between-subject variable and test time as a within-subject variable. Results show that both conditions demonstrated significant learning results ($F(1, 28) = 50.244$, $p < 0.001$), but there was no significant difference between conditions ($F(1, 28) = 0.18$, $p = 0.68$). Pretest and posttest results are shown in Table 2.

Condition	Pretest		Posttest		Normalized Gain	
	Mean	SD	Mean	SD	Mean	SD
Hyperlink	13.71	3.79	18.93	4.08	0.34	0.16
Non-Hyperlink	13.40	4.12	19.47	3.77	0.33	0.21

Table 2. Pre and posttest scores.

H2: The hyperlink feature facilitates generative strategies. The primary prediction in our work is that the navigational support and highlighting of key information in both views provided by the hyperlink feature would yield more connections among different concepts as well as more references and comparison between the textbook and the concept maps. Table 3 shows three indicators of generative strategies and the overall generative score.

We conducted a MANCOVA with the above features of generative strategies as dependent variables, and condition as an independent variable. We used total actions as a covariate, as a proxy for how active students were when interacting with the application. The overall model was significant between conditions, $F(3, 25) = 13.74$, $p = 0.001$, Wilks' $\lambda = 0.537$, partial $\eta^2 = 0.463$. Looking at the individual variables, back navigation ($F(1, 27) = 10.993$, $p = 0.003$, partial $\eta^2 = 0.289$) and context-switch ($F(1, 27) = 15.785$, $p<0.001$, partial $\eta^2 = 0.369$) were significantly higher in the hyperlink condition. However, number of cross-links was not significantly different between conditions ($F(1, 27) = 3.768$, $p = 0.063$, partial $\eta^2 = 0.122$). Overall, the hyperlink feature significantly increases the use of generative strategies.

Condition	Back Navigation		Cross-links		Context Switch		Overall Generative Score	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Hyperlink	34.67	11.41	13.73	10.06	114.40	55.92	0.43	0.18
Non-Hyperlink	26.93	14.03	10.47	8.13	63.60	23.77	0.28	0.15

Table 3. Variables for modeling generative strategies

H3: The use of generative strategies predicts learning outcomes. Here, we examine whether the use of generative strategies relates to learning outcomes. We represent generative strategies using the overall generative score metric, introduced in the measures section. We conducted a generalized linear mixed model with condition, overall generative score (centered by mean) and the interaction of condition and overall generative score as independent variables, and learning gain as a dependent variable. We found that the interaction between condition and overall generative score significantly affects learning gain ($F(1, 26) = 6.26$, $p = 0.019$). To explore this interaction, we performed a correlation between generative behavior and normalized gain for each condition. For the hyperlink condition, generative behaviors are positively correlated with learning ($r(13) = 0.623$, $p = 0.013$). For the non-hyperlink condition, generative behavior does not predict learning ($r(13) = -0.302$, $p = 0.274$). Thus, the more generative strategies students use, the higher their learning gain, but only in the hyperlink condition.

5 Discussion

Our study aims to evaluate how our concept map learning environment assists student in the development of generative strategies. In a study with 30 high school students, we found that the use of the hyperlink feature increases generative behaviors. While these generative behaviors were related to learning in the hyperlink condition, they were not in the non-hyperlink condition.

Students in the hyperlink condition were more likely to exhibit generative strategies within our system, comparing and connecting concepts in different segments in the book, as well as relating the concept map with the textbook. Students in the non-hyperlink condition were more likely to process the textbook material in a given linear order. The fact that hyperlink students performed significantly more generative learning behaviors reinforces our hypothesis that the navigational support and visual comparison of key information facilitates students in comparing and establishing connections among concepts across pages.

Research has demonstrated that use of these generative strategies have the potential to improve learning [14]. This is indeed what we find within the hyperlink condition, as students who exhibit more generative strategies score better on a multiple choice test. However, this is not the case in the non-hyperlink condition. We argue that benefits of generative strategies come with drawbacks, as comparing and connecting concepts located in different pages requires extraneous effort, especially when students are not provided with proper visual aids and navigational support. Unlike previous research on generative strategies, where the content used was pretty simple, consisting of only a few pages [9] [16], the reading material in our study consisted of 58 pages that students read over 5 days, imposing a much higher cognitive load. While students in the hyperlink condition are able to use to the concept map to view relevant resources, students in the non-hyperlink condition are challenged with additional effort when comparing different concepts. It is not only physically demanding, as they have to flip through several pages manually, but also cognitive challenging due to the complex content structure. The benefits of using generative strategies are more likely to be hindered by the high cognitive load caused by the inefficient navigation. Thus, to see the benefits of generative strategies, proper visual aids and navigational support need to be given to students.

Our study has some limitations. The total sample size of the study is 32, with 30 used for analysis. Although the results suggest a significant difference in the generative learning behaviors between conditions, the overall effect might be not representative of the population due to the insufficient sample size. In addition, following the teacher's regular practice, the pre and posttests consist of the same questions in different orders, and thus there may have been a testing effect. Further, to adapt the class schedule, our study lasted 20 minutes per day for 5 days, leaving the students another 20 minutes for other class activities like group projects, presentations, etc. These additional resources might have caused unpredictable variance within the learning effects. Nevertheless, we believe our results point to the need for future research on how generative strategies can be supported within interactive learning environments.

6 Building an Intelligent Model

Based on our results, we can build an intelligent model that assesses in real-time whether a student is pursuing generative strategies. The core part of our system is the constraint modeler, which compares student interactions with a set of pre-defined constraints and determines what constraint students violate. Based on the overall generative score metric developed above, we propose potential constraints as follows:

1. x% of the links in the concept map are cross links.
2. Student navigates to previous pages after reading y pages consecutively.
3. Student adds concept map nodes after reading z pages.
4. Student switches attention between concept map and textbook after k actions.
5. Student uses the hyperlink feature every t actions.

Here, variables x, y, k, z, t depend on the learning context, for example, total pages of the textbook, learning proficiency of students, learning period, and objectives. Within our context, we can infer some possible values based on the behavioral data from the hyperlink condition. In the hyperlink condition, the average cross link percentage is 44.73. Thus, we can use 44.73 as a base value for x. Depending on different goals and objectives, these parameters can be varied. For example, a base value for x is 44.73, but when assisting students with less experience with generative strategies, we can lower x to prevent the system from giving extensive feedback. Based on the discussion above, we believe that it may be highly beneficial to provide feedback based on these constraints. In our system, constraints are evaluated after every student action and a student model is updated in real time. Feedback is given when the student model exceeds a certain threshold. For example, if a student constantly reads consecutively without navigating back, which violates constraint 3, a possible feedback message would be "I noticed you've been reading for a while. Are there any important concepts that you would like to add to the concept map?"

Our proposed system leverages research on constraint-based tutoring systems [20] to offer an efficient way of modeling generative learning in concept mapping, but differs from traditional constraint-based models (CBM) in the ways constraints are used and feedback is given. Traditional CBMs are developed based on Ohlsson's theory of learning from performance errors [17] and constraints are assessed during each problem solving state and feedback is given after each task. However, providing feedback on generative strategies might be more helpful if it's immediate, that is, as students are constructing the concept map. Therefore, in our system, constraints are used to evaluate student behaviors and we update the student model in real time.

In this work, we have discussed how navigational support and visual aids in concept mapping supports generative learning. The strength and novelty of our system lies in its ability to facilitate student in comparing and connecting concepts across pages. Although our study has some limitations, our results indicate that the hyperlink feature facilitates generative strategies, and the use of generative strategies in concept mapping relates to more learning when proper navigational aid is given. Based on these findings, we propose a constraint based feedback system that has the potential to support students in developing generative leaning strategies. These findings suggest future promising opportunities for developing adaptive technologies to support generative strategies during a variety of learning activities.

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7 References

1. Vekiri, Ioanna. "What is the value of graphical displays in learning?." *Educational Psychology Review* 14.3 (2002): 261-312.
2. Winn, William. "Learning from maps and diagrams." *Educational Psychology Review* 3.3 (1991): 211-247.

3. Novak, Joseph D., and Alberto J. Cañas. "The theory underlying concept maps and how to construct and use them." (2008).
4. Davies, Martin. "Concept mapping, mind mapping and argument mapping: what are the differences and do they matter?." *Higher education* 62.3 (2011): 279-301.
5. Chang, Kuo-En, Yao-Ting Sung, and S. F. Chen. "Learning through computer-based concept mapping with scaffolding aid." *Journal of computer assisted learning* 17.1 (2001): 21-33.
6. Hirashima, Tsukasa, et al. "Kit-build concept map for automatic diagnosis." *International Conference on Artificial Intelligence in Education*. Springer Berlin Heidelberg, 2011.
7. Wu, Po-Han, et al. "An innovative concept map approach for improving students' learning performance with an instant feedback mechanism." *British Journal of Educational Technology* 43.2 (2012): 217-232.
8. Grabowski, B. L. Generative learning: Past, present, and future. In D. H. Jonassen (Ed.), *Handbook of research for educational communications and technology*, (1996): 897-913.
9. Ponce, Hector R., and Richard E. Mayer. "Qualitatively different cognitive processing during online reading primed by different study activities." *Computers in human behavior* 30 (2014): 121-130.
10. Cañas, Alberto J., et al. "CmapTools: A knowledge modeling and sharing environment." Concept maps: Theory, methodology, technology. *Proceedings of the first international conference on concept mapping*. Vol. 1. 2004.
11. Zeiliger, Romain, Thérèse Reggers, and Robert Peeters. "Concept-map based navigation in educational hypermedia: a case study." *Proceedings of ED-MEDIA*. Vol. 96. 1996.
12. Puntambekar, Sadhana, Agnes Stylianou, and Roland Hübscher. "Improving navigation and learning in hypertext environments with navigable concept maps." *Human-Computer Interaction* 18.4 (2003): 395-428.
13. Kinchin, Ian M. "If concept mapping is so helpful to learning biology, why aren't we all doing it?." *International Journal of Science Education* 23.12 (2001): 1257-1269.
14. Wittrock, Merlin C. "Generative learning processes of the brain." *Educational Psychologist* 27.4 (1992): 531-541.
15. Ritchie, Donn, and Chris Volkl. "Effectiveness of two generative learning strategies in the science classroom." *School Science and Mathematics* 100.2 (2000): 83-89.
16. Doctorow, Marleen, Merlin C. Wittrock, and Carolyn Marks. "Generative processes in reading comprehension." *Journal of Educational Psychology* 70.2 (1978): 109.
17. Ohlsson, Stellan. "Learning from performance errors." *Psychological review* 103.2 (1996): 241.
18. Nesbit, John C., and Olusola O. Adesope. "Learning with concept and knowledge maps: A meta-analysis." *Review of educational research* 76.3 (2006): 413-448.
19. Weinbrenner, Stefan, Jan Engler, and H. Ulrich Hoppe. "Ontology-supported scaffolding of concept maps." *International Conference on Artificial Intelligence in Education*. Springer Berlin Heidelberg, 2011.
20. Mitrovic, Antonija, Kenneth R. Koedinger, and Brent Martin. "A comparative analysis of cognitive tutoring and constraint-based modeling." *International Conference on User Modeling*. Springer Berlin Heidelberg, 2003.
21. Hake, Richard R. "Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses." *American journal of Physics* 66.1 (1998): 64-74.
22. Jain, Anil, Karthik Nandakumar, and Arun Ross. "Score normalization in multimodal biometric systems." *Pattern recognition* 38.12 (2005): 2270-2285.