MindDot: Supporting Effective Cognitive Behaviors in Concept Map-Based Learning Environments

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ABSTRACT

While prior research has revealed the promising impact of concept mapping on learning, few have comprehensively modeled different cognitive behaviors during concept mapping. In addition, existing concept mapping tools lack effective feedback to support better learning behaviors. This work presents *MindDot*, a concept map-based learning environment that facilitates the cognitive process of comparing and integrating related concepts via two forms of support, a hyperlink feature and an expert template. Study results suggested that the hyperlink support had a positive impact on the development of comparative strategies and enhanced learning, while the template support had marginal effects on learning. We further evaluated the cognitive process at a fine-grained level with two forms of visualizations. We then extracted several behavioral patterns that provided insights about the cognitive process in learning. Lastly, we derive design recommendations that we hope will inspire future concept map-based learning systems that evaluate students' learning processes and adaptively support them in developing effective learning behaviors.

CCS CONCEPTS

• Human-centered computing~Empirical studies in HCI
• Applied computing~E-learning
• Information systems~Multimedia content creation

KEYWORDS

Concept Mapping; Hyperlink Navigation; Expert Template; Comparative Strategy; Data Visualization; Behavioral Patterns

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1 INTRODUCTION

Concept maps are visual representations that illustrate knowledge structures, in which key concepts are denoted as labeled nodes and relationships among them are denoted as labeled links [25]. Having students construct and use concept maps to develop an understanding of important domain ideas has been shown to have many benefits. Horton et al [12] conducted a meta-analysis of 19 classroom-based studies on concept mapping and reported that concept mapping had positive effects on learning outcomes, raising individual student achievement on average by 0.46 standard deviations. Concept mapping has also been shown to have impact on students' domain-general skills, such as problem-solving [26], collaboration [29, 20, 17], and self-regulation [6].

During concept mapping, students learn by actively identifying important concepts and explicitly establishing relationships among them [25]. In a study comparing learning via concept mapping and learning via note-taking, students in the concept mapping condition were more likely to use a **comparative strategy**, where they processed the content by actively comparing concepts from different segments in the text [26]. In contrast, students in the note-taking condition were more likely to use a linear strategy, in which they passively processed the content in a given linear order. The use of a comparative strategy has been broadly found to be an important component of learning and comprehension in concept mapping [32]. However, the use of concept mapping comes with certain limitations. Concept mapping is rarely used spontaneously by students, as the process of modifying and organizing a high-quality concept map is messy and cumbersome [1]. Creating a high-quality concept map requires training and expertise so that students do not feel overwhelmed and de-motivated [7, 14]. Lim et al. [16] also pointed out that students with low self-regulation skills are likely to benefit less from concept mapping tasks.

The careful design of computer-based concept mapping tools may be one way of supporting students during concept mapping activities, and of improving the benefits of these activities. In general, members of the CHI community have demonstrated how technology design can improve learning strategies across a variety of applications, from using a smartwatch as a tool for situated reflection [10] to using gamification to improve self-evaluation [8]. In a similar vein, several freely available computer-based concept mapping tools have been developed to support concept mapping [4, 22, 23]. These tools have demonstrated significant advantages over traditional concept mapping tasks [4], by focusing on making the mechanics of constructing concept maps easier. However, many of these tools only provide superficial features like fast input, and do not fully leverage the capabilities of computer technologies to support the learning process. In contrast, computer-based approaches explored in research directly support learning during concept mapping. For example, there has been much research into providing students with incomplete concept map templates prepared by instructors [18], or on providing students with diagnostic feedback on the structure and content of the maps themselves [11]. Although these works have also demonstrated positive impacts, they only focus on the quality of the final products students make. Other research has explored supporting the cognitive process during map construction. For example, Betty's brain [15] is an intelligent teachable agent that allows students to construct concept maps through a "learning by teaching" manner. The system supports self-regulation and learning strategies by guiding students to refine their maps via metacognitive feedback. In this work, we aim to offer a different kind of metacognitive support. We focus on assisting students in the development of comparative strategies, that is, the process of navigating the content, identifying key concepts and establishing relationships among them. This work builds on our previous research [32] that demonstrated the benefits of a **hyperlink** feature in concept mapping, where nodes in the concept map that students are constructing are hyperlinked to the content that the nodes represent. This feature created a coherent connection between the content and the concept map, allowing students to tap on nodes to read related content, and making it easier for students to review and compare concepts located in different segments in the text.

In this paper, we present *MindDot*, a digital learning environment that enhances support in concept mapping by introducing an expert template feature in conjunction with the hyperlink support. While prior research has revealed positive impacts on both features, each has its limitations. Our prior work [32] demonstrated that the hyperlink feature promoted comparative strategies, but no significant learning improvements were found. As Puntambekar pointed out [28], map-based navigations might not always be effective. The flexibility and nonlinearity in hypertext navigation might cause confusion and disorientation [19]. Thus, proper guidance such as hints or expert explanation is needed to enhance the quality of hyperlink navigations. Similarly, although research has reported benefits of template-based support [5], a major drawback is the additional workload caused by the unfamiliar structure [14]. Therefore, reducing the effort of understanding the template is critical to enhancing the benefit of template-based support. The novelty of this work is the integration between the hyperlink and template support, which has the potential to reduce limitations discussed above and also amplify the benefits of both approaches. With the support of the hyperlink feature, students can process the template by tapping on template nodes to review relevant information. The key concept nodes contained in the template might provide a navigational guide for students, pointing towards the locations of potential concepts and relationships to be added. With the support of the expert template, hyperlink navigations can be made more meaningful and more aligned to learning goals. Therefore, we envision that the hyperlink and template support together would further facilitate the development of comparative strategies.

We conducted a study with 59 undergraduate students that evaluated the combined effects of the hyperlink and template features on their learning. As part of this study, we assessed both student comparative strategies and the quality of their final concept maps. In the study, we found that hyperlink support improved comparative strategies and learning outcomes. We then evaluated the use of comparative strategies during concept map construction via two visualizations and found certain learning characteristics and behavioral patterns that lead to higher learning outcomes. We close the paper with design recommendations for future concept mapping systems to better leverage computer technologies to support the cognitive process of concept mapping.

The primary contributions of this paper are: (1) *MindDot*, an interactive concept map-based learning environment that integrates learning content with a concept mapping tool and facilitates the development of comparative strategies via an innovative integration of hyperlink and template support. (2) A controlled study revealing that *MindDot* had significant impact on both learning achievements and the development of comparative strategies. (3) A deeper understanding of how to model comparative strategies, which student actions indicate comparative strategies, and the relationship between comparative strategies and learning. (4) Design recommendations for future computer-based concept mapping systems that support effective learning strategies.

2 RELATED WORK

2.1 Computer-Based Concept Mapping

While concept mapping has been shown to be a beneficial learning activity, the traditional pen-and-paper approach has limitations. Editing and revising the map takes considerable amounts of extraneous cognitive load [13] and it can be difficult for instructors to evaluate students' maps and provide appropriate feedback [5].

The introduction of personal computers enabled the development of computer-based concept mapping tools. For instance, CmapTools [4] is a software environment that empowers learners to construct concept maps both individually and collaboratively. CmapTools has been widely used by various research in the field as a foundation for concept map construction [9, 3, 23]. Similar online concept mapping tools such as MindMaple [23] and Mind Vector [22] have also been developed to support concept map construction. Others have implemented mobile learning environments for concept mapping [13]. These tools tend to provide features like fast input, easy modification, map sharing, and customization, and have demonstrated significant advantages over pen-and-paper concept mapping tasks [4]. However, there may be an opportunity to see greater gains by directly supporting the cognitive processes involved in concept mapping.

2.2 Concept Map Templates

In contrast, an approach that both makes concept mapping more efficient and provides cognitive support is a **template** approach, often referred to as "expert skeleton" concept maps [25]. In this approach, students are presented with an incomplete concept map and asked to extend it or fill in missing nodes [5]. These templates are designed to serve as a basic foundation that grounds certain key concepts and at the same time, provides cues about missing concepts and relationships in the structure. Previous work has revealed the benefits of providing templates to support concept mapping [5][18]. However, a major concern with this approach is the additional effort required to process the external template structure. Kinchin [14] theorized that learners who are confronted with ready-made complex maps might initially feel overwhelmed by the unfamiliar structure and connections. In our work, we augment the template approach with a hyperlink feature, where students can use each hyperlinked concept to navigate to the page

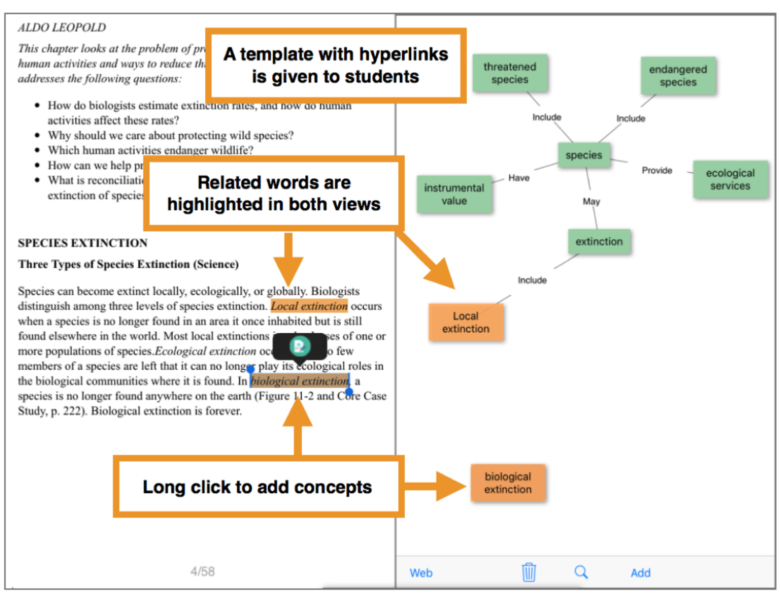

Figure 1. Screenshot of MindDot, supporting concept mapping through hyperlink navigation and an expert template.

where the concept was created. This approach may help students process the template by connecting each template node to relevant textual information.

2.3 Concept Map-Based Navigation

To support the process of reviewing and comparing key concepts, other research has explored using concept maps as navigation tools via the introduction of hyperlinks. Zeiliger et al. [33] offered students concept maps for navigation in a hypermedia learning system, with the goal of assisting learners to construct their own visions of the domain and establish better connections between concepts. Nonetheless, the experiment showed that students with the concept map-based navigation performed the same as those without support in the learning assessments. Puntambekar [28] gave students a pre-made concept map that was used as a navigational guide to the hypertext learning content. Results showed that students with the navigational support visited more concepts that were relevant to the learning goal. However, no significant learning difference was found between the support condition and no support condition. Much of the work on concept-based navigation used a pre-made framework prepared by instructors. As we discussed previously, unfamiliar concept map structures are likely to cause additional cognitive effort for students and thus, reducing the benefits of flexible navigation.

In contrast, our previous work revealed the benefits of concept map-based navigation with the support of a hyperlink feature, which allows students to navigate the content using maps themselves have constructed [32]. Students construct concept maps from scratch and use them as navigational anchors. Similarly, Liu et al [16] proposed a system ConceptScape that allows learners to generate concept maps from a video. Nodes created are hyperlinked with time stamps and can be used to navigate the video. However, the confusion and disorientation caused by the flexibility and nonlinearity during navigation still remain to be solved. This work enhances previous research on concept map-based navigation by integrating template support with the hyperlink feature. As we discussed in the introduction, combining the hyperlink feature with template support might enhance the positive effects of both features. These enhanced features offer both navigational aids and cues about potential relationships between concepts, which have great potential in facilitating the processes of searching for key concepts and establishing relationships among them. Thus, the integration of the two features may better support comparative strategies and promote learning from concept mapping.

3 System Design

This work uses *MindDot*, an iPad-based interactive concept mapping learning environment integrated with a digital textbook. The system is written in Objective-C and runs on iPad devices. Textbooks displayed in the system are written in .epub format, which is a commonly used format in digital textbooks. The system has a dual window layout, where the left side displays the learning content and the right side shows the concept mapping view (see Figure 1). Students create concept nodes through a "click-to-add" gesture. When students read the content and identify an important concept they would like to add to their concept map, they long press on the word and select the "add concept" button. Links with other concept nodes can be added by long pressing on the node, select the linking option, and tapping on a related node. If they choose, students can edit the name of their added concept node, or add their own nodes by clicking the "+" button on the function bar. Students can also delete concept nodes as needed.

Our system has two key features explicitly designed to facilitate the use of comparative strategies: The **hyperlink** feature and the **template** feature. With the dual window layout, all the nodes created in the application are hyperlinked with related book pages. Students can revisit the page where a node was created anytime by simply tapping on that node. If a node is created through the "click-to-add" gesture, the word that is used to create the node will be highlighted along with the node itself, pinpointing where this concept is mentioned in the textbook. Highlights are context-sensitive; as students navigate in the book view (swiping right or left), the highlighted words and concepts will show them which concepts were created on the student's current page. We hypothesize that students with the hyperlink feature will navigate the content in a more flexible and personalized way. This flexibility in navigation allows students to more easily compare concepts located in different pages, and thus, establish a more concrete and interconnected knowledge structure.

When students first load the application, the system provides students with an incomplete expert template as a support for their concept mapping activity. The template presented in the study was created by the authors of the paper, and consists of 8 key concept nodes and 7 links connecting them. The nodes are created from 6 different pages and 5 of the links are cross-links, each connects two concept nodes from different pages of the content. The nodes and links were selected to form a basic framework of the key concepts in the content and are easy to expand on.

All the nodes in the template are hyperlinked to relevant pages. With the navigational support provided by the hyperlink feature, students can tap on the nodes in the template and read related content (aided through the keyword highlighting in the text). This feature has the potential to reduce the effect of processing and understanding the template structure. At the same time, the template serves as a navigational framework, guiding students to pay attention to where those key concepts are mentioned in the content.

4 USER STUDY

4.1 Hypotheses

To comprehensively examine how the hyperlink feature and the template facilitate comparative strategies during concept mapping and how they affect learning, we conducted a controlled study, in which students read a section of an earth science textbook chapter and constructed a concept map using our application. Pre and posttests were given to students and log data was collected to investigate students' interactions with the system and their corresponding learning outcomes. Based on the discussion presented above, we hereby propose three hypotheses: H_1: The hyperlink and template support improve learning. H_2: The hyperlink and template support facilitate the development of comparative strategies. H_3: Student use of comparative strategies is more predictive of learning outcomes than the quality of their concept maps.

4.2 Method

We recruited 60 undergraduate students for the study. However, one student's posttest form was lost during data collection. Thus, for the data analysis, 59 students (19 male and 40 female) were used. *MindDot* was installed on an iPad 2 Air with a 9.7-inch retina display and a multi-touch interface. The learning material consisted of the chapter *Sustaining Biodiversity: The Species Approach* from a science textbook [21]. The textbook chapter displayed in the application was manually edited by us to fit the screen of the iPad. The entire chapter was 10 sections spanning 58 pages; in the study, however, due to the limited time, students were only required to read the first 20 pages of the given content (4 sections).

The goal of our study was to test the effect of the hyperlink and template support. There were four conditions:

1. **Hyperlink + template (*H+T*):** In this condition, students had the hyperlink and template features discussed above. Students with the template built their concept map based on the given structure. However, students had the ability to make edits to the template to better fit their own understanding.
2. **Hyperlink alone (*H*):** In this condition, students still had the hyperlink feature for navigation and highlighting, but they constructed their concept maps from scratch.
3. **Template alone (*T*)**: Student in this condition did not have the hyperlink feature for navigation, but they received the same expert skeleton template as the *H+T* condition. However, the template in this condition had no hyperlinks, nor were the related keywords in the template and text highlighted during navigation.
4. **No hyperlink or template (*N*)**: In this condition, students still constructed concept maps with the click to add feature while reading the material. However, they received minimum cognitive support as they had neither the hyperlink feature nor the incomplete template.

Students were randomly assigned to conditions, with 15 in condition *H+T*, 14 in condition H, 15 in condition T and 15 in condition *N*. Students began the study with a pretest, which consisted of 12 multiple choice questions. After the pretest, all participants were given a 5-minute in-app training session (tailored to condition) where they learned about how to use the application features through a step-based tutorial. Students were then asked to take 30 minutes to read the content and leverage all the features mentioned in the training to create the best concept map they could. If students finished reading the content before 30 minutes, they were told to refine their maps. We asked students to stop their concept map construction after the 30-minute learning stage and spend another 5 minutes to use the map as a review tool to prepare themselves for the posttest. The posttest was given after the review stage and consisted of the same questions as the pretest along with a 3-question transfer assessment.

4.3 Measures

Learning. The pretest and posttest questions were designed by a high school teacher that we worked with in a previous study. The pretest consisted of 12 multiple choice questions, and the posttest consisted of the same questions but in a different order. 10 of the multiple choice questions were specifically covered in the learning content and were used as main assessment questions to measure learning and the other 2 were not covered in the content and were used as control questions to measure the effect of students' ability to guess the correct answers.

Comparative strategies. Comparative strategies refer to behaviors and activities that contribute to the comparison of different concepts and the construction of a coherent knowledge structure. Following our previous work [32], we model comparative strategies within our particular learning environment using the following three variables. In this analysis, student actions in the review sessions are excluded.

1. *Back navigation.* An important characteristic of a comparative strategy is the comparison among different concepts. In a reading context, it is reflected as attention switches in different parts of the book. In our system, the epub book was custom made to fit the iPad screen. The original chapter had 27 pages and the iPad version had 58 pages. Therefore, key concepts in the material are scattered in different pages. To review relevant content and make connections, learners will need to go back and forth between pages. Thus, we consider back navigation as a proxy for comparative strategies. 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. Hyperlink navigations where students move back in the text are also counted as back navigations.

2. *Cross-links.* A cross-link is a concept link that connects two concept nodes from different pages of the content. These can be beneficial to student comprehension as they often represent creative inferences relating to different parts of the knowledge framework. They are critical elements in knowledge structures and are good indications of comparative strategies. Thus, for each student, we compute the number of cross-links as an indicator of the comparative model. For the students who received the template support, cross-links in the pre-made templates were not counted.

3. *Context switch.* In order to establish connections between concepts while constructing the concept maps, students will need to constantly refer to the learning content. Thus, how often students are referencing the learning material during concept mapping would be another indication of comparative strategies. Here, we compute context switches, that is the number of times students' attention switches from the textbook view to the concept map view. Our log file records which view students are interacting with for each action and every time a student switches from one view to another, it is counted as a context switch.

Concept map evaluation. A key element of this work is looking at the concept mapping process in contrast to concept mapping outcomes. Thus, we also collected metrics related to the final product of the activity. First, we counted the number of nodes students added and the number of links they created. Then, we graded students' concept maps by computing how many concepts covered by the test questions were being correctly added. To do this, we mapped the 10 main assessment questions into 21 connected concept nodes. For each question, we manually checked if these corresponding nodes were correctly added in students' maps. When a student correctly adds all the required nodes from a test question, we give the student 1 point for that particular question. Nodes newly created need to be linked to related nodes with valid relationships in order to be considered as correct. Nodes students add that are not part of the 21 key nodes were not scored. The final concept map score is computed as the sum of all the corresponding scores from the 10 assessment questions. In the template condition, students are given a template that contains 8 of the 21 key concepts measured in the assessment questions. We therefore exclude the 8 nodes given in the template and compute the coverage of the remaining 13 nodes in the map.

4.4 Results

H_1: The hyperlink and template support improve learning. A repeated-measures ANOVA on test scores with test time as the within-subjects' variable showed that students demonstrated significant learning between the pretest and posttest across all conditions ($F(1, 55) = 10.97$, $p = 0.002$). Results are presented in Table 1, including 2 control questions and 10 main assessment questions.

Table 1. Mean pre and posttest scores. Standard deviations are in parentheses

Condition	Pretest		Posttest	
	Control Questions	Main Questions	Control Questions	Main Questions
H+T	0.40 (0.63)	7.27 (1.62)	0.13 (0.35)	8.60 (1.05)
H	0.50 (0.65)	7.85 (1.70)	0.29 (0.47)	8.64 (1.78)
T	0.44 (0.51)	7.94 (1.84)	0.60 (0.51)	8.38 (1.40)
N	0.21 (0.45)	7.57 (1.22)	0.07 (0.27)	7.42 (1.15)

We further conducted an ANCOVA test with the hyperlink and template feature as the independent variables, posttest as the dependent variable and pretest as the covariate. The hyperlink feature had a significant impact on learning (F(1,55)=7.54, p=0.008, η_p^2=0.123). A marginal effect was found on learning with the template support (F(1,55)=2.93, p=0.093, η_p^2=0.052), and no effect was found on the interaction between the hyperlink and template support (F(2,54)=0.762, p=0.387, η_p^2=0.014). In contrast, a similar repeated-measures ANOVA on the two control questions revealed that for the control questions, there was no significant learning between the pre and posttest (F(1, 55) = 2.42, p = 0.125). An ANCOVA test on the control questions revealed no significant effect on the hyperlink feature (F(1,55)=1.466, p=0.231, η_p^2=0.03) and the template feature (F(1,55)=2.230, p=0.141, η_p^2=0.04). There was an effect on the interaction between the hyperlink and template feature (F(1,55)=7.50, p=0.008, η_p^2=0.12). Nevertheless, it is unlikely that effects on the main assessments were due to students' ability to guess the correct answers to the questions or a testing effect. H_1 was partially supported, as the hyperlink feature significantly improved learning and template feature had marginal benefits.

H_2: The hyperlink and template support facilitate the development of comparative strategies. Table 2 shows the means and standard deviations for the three components of comparative strategies that we are tracking as well as the total number of actions.

Table 2. Indicators of comparative strategies. Means are presented, with standard deviations in parentheses.

Condition	# Back Navigation	# Cross-link	# Context Switch	#Action
H+T	20.13 (12.76)	13.60 (6.42)	82.27 (25.22)	357.2 (134.7)
H	32.42 (20.42)	7.86 (5.79)	105.7 (51.79)	449.1 (213.7)
T	12.86 (12.76)	13.38 (5.45)	51.38 (20.49)	367.3 (103.8)
N	15.07 (9.40)	7.57 (5.83)	42.71 (15.71)	350.1 (105.7)

We conducted generalized linear models on each factor in the comparative strategy model with the two types of support (hyperlink and template) as independent factors and total number of actions as a predictor variable, a proxy for how active students were when interacting with the application. All two-way interactions were included in the model. Data used here represent absolute counts of the three factors. The template support had no effect on back navigation (F(1, 58) = 0.04, p =0.86), context switch (F(1, 58) = 2.10, p = 0.15) and cross-link (F(1, 58) = 2.34, p = 0.13). The hyperlink support had no effect on back navigation (F(1, 58) = 1.50, p = 0.23), context switch (F(1, 58) = 0.29, p = 0.60) and cross-link (F(1, 58) = 0.54, p = 0.47). The interaction between the hyperlink feature and the template feature had no effect on back navigation (F(1, 58) = 0.21, p = 0.65), context switch (F(1, 58) = 1.60, p = 0.21) and cross-link (F(1, 58) = 0.45, p = 0.51). The interaction between the hyperlink feature and total actions had significant effect on back navigation (F(1, 58) = 6.41, p = 0.014) and context switch (F(1, 58) = 5.05, p = 0.029) and no effect on cross-link (F(1, 58) = 0.53, p = 0.47). The interaction between the template and total actions had no effect on back navigation (F(1, 58) = 0.50, p = 0.48), context switches (F(1, 58) = 2.34, p = 0.13) and cross-link (F(1, 58) < 0.001, p = 0.99).

Table 3. Marginal means of back navigation and context switch at M-SD, M, and M+SD total actions.

		Mean - SD	Mean	Mean + SD
#Back Navigation	H	13.10(2.64)	24.42(1.98)	36.43(2.42)
	NH	11.32(3.16)	13.92(1.94)	16.69(3.32)
#Context Switch	H	62.68(4.74)	89.67(3.56)	118.30(4.35)
	NH	34.07(5.67)	47.47(3.48)	61.67(5.96)

The marginal means for the hyperlink by total actions interaction are shown in table 3. We can see that as total actions increase, the difference between conditions becomes more prominent. H_2 was partially supported, as the interaction between the hyperlink feature and total actions affected back navigations and context switches.

H_3. Student use of comparative strategies is more predictive of learning outcomes than the quality of their concept maps. Here, we evaluated the effect of comparative strategies on learning. We conducted a partial correlation, where we control for pretest score on the 10 main assessment questions, and then examine the relationships between the main posttest score and the three measures of comparative strategies. Results indicated that all three variables in the comparative model were significantly correlated with learning: cross-links ($r(56)$=0.26, p=0.049), back navigations ($r(56)$=0.36, p=0.005) and context switches ($r(56)$=0.39, p=0.002).

We then explored the relationship between concept map nodes, links, scores and learning. Table 4 shows the number of nodes added, number of links added, and map scores across conditions. A one-way ANOVA test revealed no effect of condition on number of nodes ($F(1, 58) = 0.93$, $p = 0.43$) or number of links ($F(1, 58) = 0.55$, $p = 0.65$). Partial correlations (controlling for pretest) indicated that posttest was not correlated with number of nodes ($r(56)=0.16$, $p=0.23$), or number of links ($r(56)=0.20$, $p=0.11$). As we used different scoring methods for the template condition and non-template condition, the map score was different between conditions ($F(1, 58) = 27.13$, $p < 0.001$). Thus, we computed those correlations separately. For the template condition, the map score was marginally correlated with posttest score ($r(27) = 0.338$, $p = 0.07$). For the non-template conditions, the map score did not affect posttest score ($r(27) = 0.119$, $p = 0.545$), controlling for pretest.

Table 4. Concept map evaluation for each condition. Means and standard deviations are presented.

Condition	# Nodes	# Links	Map Score
H+T	12.87 (7.51)	12.40 (8.86)	2.73 (2.15)
H	18.07 (10.92)	15.00 (10.29)	4.57 (1.02)
T	16.33 (8.70)	15.67 (9.80)	1.73 (1.03)
N	16.47 (7.30)	12.07 (8.80)	4.40 (1.55)

To summarize, all three comparative strategy variables were correlated with learning, while the map score in the template conditions marginally predicted learning. None of the other concept mapping variables were significantly correlated with learning.

5 UNDERSTANDING THE CONCEPT MAPPING PROCESS

The comparative strategy metric presented above provides a general understanding of different behavioral characteristics of comparative strategies, and was shown to be influenced by our manipulations and predict learning. However, the metric aggregates student behaviors over the course of the whole session, rather than providing insight into how the learning behaviors are used in sequence. To develop an action-by-action understanding of comparative strategies, we evaluate students' process of constructing concept maps through two types of visualizations: **Sequence diagrams** and **Navigation path diagrams**.

5.1 Sequence Diagram

The sequence diagram decomposes the whole concept mapping activity into several sequences of actions, where each sequence includes the behaviors that students perform when creating a concept node (Figure 2). In the sequence diagram, we consider the overall concept mapping task as combinations of three high-level actions: reading, adding and linking nodes. Adding node actions are used to delimitate the start and the end of each sequence. Thus, every time students finish creating a node, we start a new sequence, and that sequence is comprised of all their actions until they create the next node. To distinguish whether students were performing comparative strategies in reading and linking behaviors, we further sub-coded them into the following four categories:

1. **Read (R).** Read actions mean that students are processing the content by following the linear order presented in the material. It represents one forward navigation in the text.
2. **Compare (P)**. The compare action represents one back navigation (hyperlink navigations where students move back are also counted). It indicates that students may be making comparisons between concepts in the content.
3. **Link (K).** A link action happens when a student connects two concept nodes that are created on the same page.
4. **Cross-link (C)**. Cross-link actions are when students link two concepts from different pages. Creating cross-links may indicate comparisons among concepts.

Each sequence diagram begins with a starting state "S" and ends with an ending state "E". In between the starting state and ending state, we present 20 rows of states, as most sequences contain less than 20 numbers of actions. Each

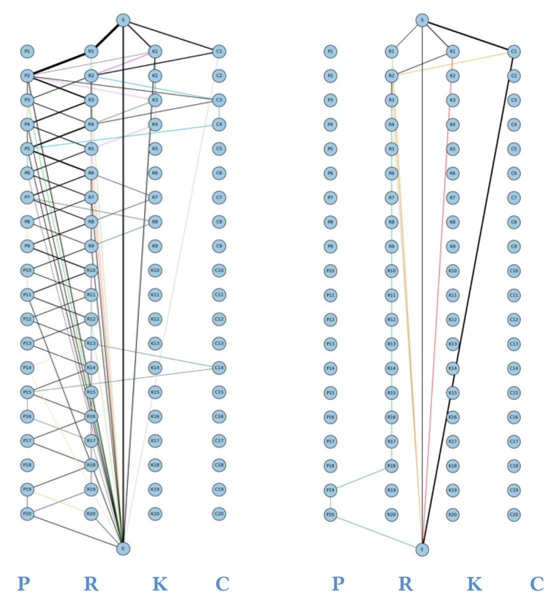

Figure 2. (left) Action sequences from a high learning student (right) action sequences from a low learning student.

row has the four classified states (P, R, K, C) discussed above. When students start using the system or just finished creating a node, a new sequence is generated from the starting state "S". For each following action students perform, we classify it into the 4 categories presented above and draw a line from the current state to the corresponding state in the next row. When students create a concept node after a series of actions, we end the sequence and draw a line to the ending state "E". Each sequence is represented as a path with a unique color. If paths have overlapping sections, we change the color of the overlapping part into black. The thickness of the lines is a visual indicator of the number of times students took that path.

We created a single sequence diagram for each student. We then put the 10 students who had the highest learning gains into a high-learning group and put the 10 students who had the lowest learning gains into a low-learning group. We visually inspected the diagrams for the high and low learning groups. Figure 2 shows two prototypical diagrams. 2a represents a high learning student from the hyperlink condition (1 on normalized learning gain), and 2b represents a low learning student from the template condition (-0.1 on normalized learning gain). There was a clear general difference in behavioral patterns between the high learning students and the low learning students. In the high learning diagrams, vertical lengths of the overall interaction paths are much longer than the low learning ones, suggesting that students with high learning gains are likely to perform more meaningful behaviors before creating nodes. Additionally, in the high learning diagrams, there are more horizontal switches (e.g., P to K, P to C, R to K). These horizontal switches in the high learning diagram indicate that students benefit more from cross-links if they carefully read and compare those related concepts in the content when creating links. In contrast, in the low learning diagrams, there are few meaningful behaviors made when creating nodes. Most of the sequences end within 3 levels. Although students in the low learning group also created cross-links, they created cross-links immediately after they added a node, without any reading and comparing behavior. Based on the discussion above, we identify a set of three promising patterns in student' concept mapping behavior. These patterns do not encompass all solving behavior in *MindDot*, but instead, capture key instances of strategic behavior in concept mapping.

Read and Compare (RC). As shown in Figure 2 (left), high learning students had more interactions and switches between reading and comparing actions. This pattern indicates that it is not those individual back navigations that enhanced learning. In fact, it is the constant reading and comparing action pairs that yield positive impact on learning. Therefore, we consider the Read and Compare pattern as a positive pattern.

Read and Link (RL). The sequence diagram demonstrated that high learning students are more likely to add links after carefully reading the content and comparing related concepts. Therefore, we consider Read and Link as a positive pattern.

Start and End (SE). in Figure 2, the low learning student had fewer direct paths between S and E, in general, low learning students had higher direct paths than high learning students. This tells us that the identification of key concepts through the addition of concept nodes would be more beneficial alongside other cognitively beneficial behaviors. The "SE" pattern is likely a negative pattern.

Table 5. Sequential pattern occurrence in the high and low learning subgroups.

Groups	Read and Compare	Read and Link	Start and End
High Learning	5.5 (3.72)	4.9 (3.07)	5.3 (1.76)
Low Learning	2.1 (1.45)	1.4 (1.43)	7.4 (3.66)

To demonstrate how students performed these patterns in the high learning and low learning groups, we counted the number of occurrences for each pattern for each student, and computed the means and standard deviations for the two groups, shown in Table 5. As we only used 10 students for each group, it is not a sufficient number to conduct a statistical analysis. Nevertheless, the means do suggest that the two positive patterns (Read and Compare, Read and Link) occur more frequently with the high learning students and the negative pattern (Start and End) is more likely to be seen with the low learning students.

To summarize, the sequence diagrams modeled comparative strategies through integrated transitions and interactions between action states, which provided more information about the cognitive process than counts of actions. For example, the sequence diagrams suggest we should be making the distinction between a student creating a cross-link after careful reading and a student creating a cross-link after little reading. Similarly, while back navigations treat all navigations to previous pages in the text as the same, the sequence diagram suggests we should be distinguishing between students who are repeatedly moving forward and back in the text to make a comparison and students who may be moving back simply to check what was on a previous page. Finally, the visualizations suggest that creating several nodes without performing other actions (represented by the SE pattern) is not beneficial, a subtlety that is not captured by the comparative strategy metric.

5.2 Navigational Path Diagram

The sequence diagrams presented above show behavior patterns students perform when creating the concept map. However, they do not contain any timing or paging information. Here, we present a second visualization: a navigation path diagram that better illustrates how students read pages and add nodes over time.

Figure 3 illustrates the navigation path of the two students used in the sequential diagram as prototypical representations of high learning and low learning students in general. The vertical axis denotes the page number and the horizontal axis illustrates the time stamps. The blue line in the graph illustrates the page order read by the student throughout the study. The "add node" action is denoted as a red dot in the diagram. The x-axis represents time and the y-axis represents the page number. Looking at the two graphs in Figure 3, one big difference between the two types of students lies in the page reading path. In the high learning students' diagrams, the page numbers gradually increase over time, but there are lots of zigzags in the reading paths, meaning that students were frequently referring to previously read content to make connections between different segments in the content. In the low learning students' graphs, the page numbers grow more smoothly. Although the students did go back to previous pages at certain points, they still passively followed the linear order presented by the content. Another difference between the high learning students and the low learning ones is how nodes were created during reading. In the high learning graphs, the red dots are spread out both horizontally and vertically, indicating that the high learning students were not only creating nodes from a wider range of pages, but also creating nodes constantly and continuously in the learning sessions. In the low learning graphs however, the red dots are more clustered towards the bottom-left corner, which means that the low learning students only created nodes in the first few pages and at the beginning of the learning stage.

This creates three additional key dimensions of student learning strategies: **vertical coverage**, **horizontal coverage**, and **zigzags**. The vertical coverage of the nodes captures how many pages of content are used by students to create their concept nodes. An indication of a high vertical coverage would be that the red dots representing adding node actions are more spread-out vertically, covering more than half of the page numbers. The horizontal coverage of the nodes denotes how often students are selecting key concepts to add to the map during the learning phase. Similarly, an indication of high horizontal coverage is that the red dots are more spread-out horizontally, covering a more than half of timestamps. The path trajectory provides additional insights about how students are comparing concepts. The high learning student had more zigzagged navigation path, suggesting that the student was constantly reviewing previously read content, while the low learning students' navigation path is smooth and more linear, indicating that the learner was passively processing the content in a linear order.

To demonstrate how students performed these visual patterns in the high learning and low learning groups, we graded each student's map by evaluating whether the map had a zigzagged path, high horizontal and vertical coverage through visual observations. We gave one point to each dimension if the map meets the definition of each dimension discussed above. Similar to the sequential pattern, we only present descriptive results, shown in Table 6. Results suggest that all three patterns are higher in the

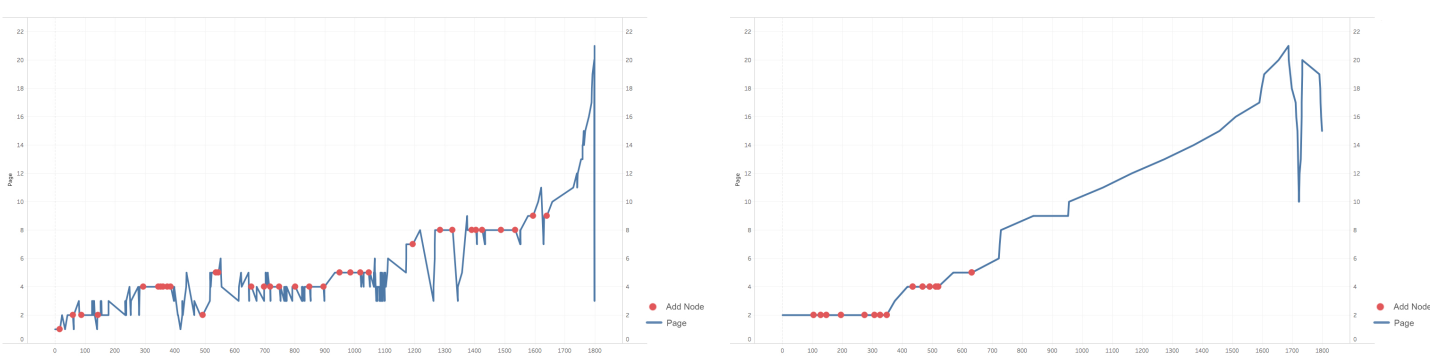

Figure 3. (a) Navigation path graph from a high learning student. (b) Navigation path graph from a low learning student.

high learning groups, meaning that high learning students are more likely to cover more text pages, refer back to previous pages, and add concepts throughout the learning session.

Table 6. Counts of students that demonstrated each visual pattern in the high and low learning subgroups.

Groups	Zigzag	Horizontal Coverage	Vertical Coverage
High Learning	8	9	7
Low Learning	2	5	5

6 DISCUSSION AND LIMITATIONS

This work aims to understand how to provide support in concept mapping to facilitate the development of comparative strategies and improve content learning. We developed *MindDot,* a computer-based concept mapping tool that supports comparative strategies through the integration of two learning features: A hyperlink feature and a template feature. A study with 59 students revealed that while both hyperlink support and template support improved comparative strategies (H_2), only the hyperlink support influenced learning (H_1). All three factors in the comparative strategy model were highly correlated with learning outcomes, while other outcome-based metrics were not (H_3). We then investigated how students employ comparative strategies in concept mapping with the help of two types of visualizations. In this section, we discuss the insights from our study and data visualizations.

6.1 Effects of Hyperlink and Template Support

In this study, we found that the hyperlink support improved both comparative strategies and learning. This is a demonstration of the power of computer-based hyperlink support for concept mapping, and suggests that this support is effective when students construct their own maps. It may indeed be that Zeiliger [33] and Putenbaker [28] did not find positive effects of hyperlinked concept maps because students were using fully complete maps that they did not construct on their own. Our result is also in contrast with our previous work [32], that took a similar approach but only found effects on comparative strategies. Our prior study took place in the classroom, and had related limitations: students engaged in learning activities other than concept mapping, and students had different levels of exposure to the concept mapping activity, due to absences. In contrast, this study was a lab study, and thus there was more control over the learning activities and time on task. Our study's higher internal validity may have increased our ability to detect effects, although the lower external validity means that a classroom study should be conducted in the future to see if the result will generalize. In addition, we found that the expert template support did not seem to be as effective at improving learning, echoing the results described in [18]. The template in our work is integrated with hyperlinks to content, aiming to reduce the effort of processing and understanding the given structure, which is a major concern with traditional pre-made templates [7].

Our results suggested that hyperlink and template support had differential effects on comparative strategies. The hyperlink support improved back navigations and context switches together with total actions. Students who were more active in the study benefited more from the hyperlink. The template support had the most effect on cross-links, although not significant. However, when examining the correlations between comparative strategies and learning, we found that back navigations and context switches were more highly correlated with learning than cross-links. Thus, the template feature may be less effective because even though it improves the number of cross-links students create, there is less of a relationship between cross-links and learning. Our sequential patterns indicated differences in outcomes between a student creating a cross-link after careful reading and a student creating a cross-link after little reading. It is possible that the template entices students to create cross-links between their own node and a template node without fully understanding the relationship between the two nodes, and thus those particular cross-links do not improve their understanding of key concepts. Chang's work [5] provided hints to students based on the comparisons between student maps and expert template found significant learning improvements. Thus, it is desirable to offer support to students when integrating their maps to the template.

We used different concept map grading methods between students in the template condition and without. Thus, it is not statistically meaningful to compare the between condition effect. Nonetheless, the map scores in the template condition had a marginal effect on learning outcomes, suggesting that with the template support, the correctness and completeness of the concept maps reflect learning outcomes. Therefore, correctly adding nodes to the expert template might have stronger learning benefits than adding to learners' own structures. Overall, characteristics of the concept maps are less predictive to learning than characteristics in the learning process.

6.2 Assessing Comparative Strategies

Building on the comparative strategy model devised in our previous work [32], the two visualizations provide additional insights into learning strategies during concept mapping, allowing us to identify specific behavioral patterns that reflect how students are making comparisons between concepts. From the sequence diagram, we extracted three behavioral patterns, with the two positive patterns showing the importance of comparisons both within the text and between the text and the concept map. This tells us that reading and comparing behaviors in the learning content are critical components in concept map-based learning environments. Our path navigation diagram evaluates comparative strategies from a different perspective, suggesting that students who read more pages, add nodes over time, and move back and forth within the text over time will benefit more. Taken together, these visualizations refined the comparative strategy metric with behavioral patterns that demote cognitive characteristics that are hard to capture by just action counts.

6.3 Insights for Future Concept Mapping Tools

Based on our findings, we propose 3 design recommendations for future concept map-based learning environments.

Integrate tools with learning content. Current concept mapping tools [4][22][23] tend to serve as external software that allow students to construct concept maps in different learning scenarios. The advantage of this approach is its compatibility with different learning contexts. However, this separation means that it is hard to provide effective scaffolding to support students' interactions between the learning content and the concept map, which is a critical component of concept mapping. The foundation of *MindDot* is the coherent integration between the learning content and the concept maps. This integration enables students to construct concept maps directly using the text in the content and in the same time, creates hyperlinks that connect nodes in the concept map with locations of key concepts in the content for navigation. This integration might also apply to the use of concept mapping with multimedia content. For instance, in online learning environments [30], one could design a concept mapping tool that allows students to use words or paragraphs from web pages to construct concept maps, and later, to use the nodes to navigate back to related content. In video-based learning environments, we could develop tools that not only connect specific nodes in the map with timestamps, as in [16], but also key objects in specific frames or additional resources related to the concepts mentioned in the video.

Provide support that doubles as an assessment. One advantage of our system is that the support we provided (e.g., the hyperlink support) allowed us to collect meaningful data about students' learning strategies. By examining how students used the hyperlinks, we were also able to make inferences about the ways in which they compared concepts. For these types of systems, it is useful to consider ways to make students' thinking visible, as first suggested by Anderson [2] in his discussion of principles for cognitive tutoring systems. By collecting sequential information on how students create concept maps, we have a real-time window into their cognitive and metacognitive processes as they attempt to make sense of the text.

Adaptively support comparative strategies. By tracking student behaviors within our system, it becomes possible to assess student comparative strategies and provide them with feedback in real time. Concept mapping activities have the potential to serve as the foundation for behavior-based intelligent tutoring systems [31] that monitor student interactions with the system and provide feedback that facilitates comparative strategies. For example, if a student has been focusing on the concept mapping view and spends less time reading (high occurrence of SE and low occurrence of RP pattern), we could provide a feedback message such as "You are doing great at building your concept map, would you like to take a break from the map and read more about the concepts in the textbook?" Much of the work in the literature has focused on providing feedback based on the quality of students' concept maps. We believe that feedback in concept mapping could be more effective if students' behaviors during the learning process are taken into consideration.

6.4 Limitations

This presented work is limited in several areas that should be investigated in future studies. First, 59 students were used for analysis. Each of the four conditions had at most 15 participants. In addition, the empirical investigation in this work was a 90-minute study conducted in a research lab instead of a classroom. Thus, a future classroom study with a larger sample size would produce results that are more representative of the population. Lastly, in our study, students were given 5 minutes to review their maps after construction, with the goal of amplifying learning benefits of concept mapping. Although actions in the review stage are excluded from the comparative strategy model, the review session might have influenced the learning effects. This study design also makes our results difficult to compare with prior studies in the field.

7 CONCLUSION AND FUTURE WORK

In this work, we presented *MindDot*, a concept map based learning environment that supports concept mapping through innovative integration of two features, hyperlink navigation and expert template. The strength and novelty of our system lie in its ability to assist students in developing comparative strategies. Our controlled study showed that students with hyperlink support outperformed the ones without hyperlink support. The system also demonstrated promising impact on supporting comparative strategies. We then presented a deeper and fine-grained understanding of how students employ comparative strategies, finding that there are indeed certain sequences of behaviors in the text (e.g., reading before adding a link) that suggest that students are making comparisons. Finally, we derive three major design recommendations for future concept mapping systems to foster the development of comparative strategies and enhancing learning outcomes: integrate tools with learning content, provide support that doubles as assessment, and adaptively support comparative strategies. Using computer-based concept mapping tools to facilitate concept mapping processes has the potential to substantially improve students' abilities to comprehend expository texts.

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