The Effects of Mind Maps on Computational Thinking

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The Effects of Mind Maps on Computational Thinking

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Abstract: Mind Maps (MM) have proven to be a practical approach that promotes meaningful learning in various domains. Yet, few works exist that investigate employing MM to blend CT across curricula. In this paper, we developed a MM approach - named Storyboard-tree - to transform "Standard/traditional" slides (SS) to the MM structure. Storyboard-tree associates the information by creating a story that chains the data with ideas and concepts which lead from the first to next and so on. The applied materials are two models in an Introduction to Computer Science (CS) course. The study utilizes two sections: one is taught with MM, and the other with SS. The observed academic results and the acceptance rate of the students and the instructors were encouraging. MM with freshman show statically significant self-efficiency scores with an approximate 50% better performance than with SS in the Algorithm concept, while all students show a statistically similar trend in the knowledge gained as well as the fondness of the approach through the self-efficiency scores. Instructor satisfaction tends to go more towards the SS approach seeing the MM implementation as not mature enough. However, the investigation concludes that the mind map technique is a feasible way to deliver CT concepts, thereby a practical approach to integrate CT into the curriculum.

Introduction
Since 2006 the popularity of computational thinking (CT) - skills for solving problems by adopting the theoretical concepts of computer science - has been increasing substantially, leading to an increase in the amount of research and experiments on the CT method. Yet, there are limited numbers of inquiry investigate approaches to incorporated CT into a curriculum. Betül Czerkawski researched ways to integrate CT across all curriculum, through surveying instructional CT designers. She constructed the survey using the ADDIE instructional design model. One of her findings showed that the Mind Map(s) (MM) strategy can establish a better connection between CT and instructional design [1]; however, very little research existed to investigate the correlation. A MM is a form of knowledge representation about a topic. It has a straightforward organizational structure that spreads from the center, including words, lines, colors, and pictures, toward an attractive, memorable diagram [2]. Previous work has shown that Mind Maps is an effective way to promote meaningful learning in various domains, including Digital Forensics [3], Cybersecurity [4] [5], Bioinformatics [6], Education [7] and more.

The primary objective of this study is to investigate the relation between MM and CT through introductory CS curriculum. Considering the nature of CS tasks, practical computing skills can be developed while nurturing an understanding of how the CT process can be applied. We propose a Storyboard-tree to associate information based on the Chain Association Method, which chains items inside a memorable story, promoting retrieval within the flow of a story. Thoughtfully planned MM efficiently direct one idea to another. Although a series of information can be reasonably remembered using only a connection
between two ideas, matching the links within a story minimizes the potential of forgetting one respect and thereby omitting the rest of the list.

Furthermore, Danny P. Wallace used the relationship, data-to-information-to-knowledge-to-wisdom (AKA DIKW pyramid), to explain a topic. The DIKW pyramid maps data such as words, numbers, and images into sentences and concepts that hold meaning and purpose is defined as information, connecting the information to relationships leads to knowledge, and applying knowledge to make judgments and decisions without thought is wisdom [8]. Moving from one level to another, looking at the data to draw some conclusions, then looking at it from different angles analyzing it piece by piece to see how those pieces related to each other is critical thinking. MM technique through which the first three levels of the DIKW pyramid can be achieved, by using data as concepts linked by relationship to produce a highly consistent diagram.

To serve the study’s purpose, MMs were integrated into a computer science course at Kansas State University. MM slides were created from the lecture materials using a Storyboard-tree, and students in the course were divided into a control group (classic method) and a research group (MM method). Study results showed success with the MM approach for juniors and first-year students with CT concepts such as algorithm and control flow. Additionally, freshmen demonstrated improved performance in decomposition and incremental and iterative concepts, showing that MM can be a practical approach for integrating CT into a curriculum.

**Background and Related Work**

**Computational Thinking**

CT has become a mainstream but dates back to the 1980s, where Seymour Papert proposed the idea of CT in his book *Mindstorms: Children, Computers, and Powerful Ideas*. He developed the programming language Logo for his envisioned learning environment Mathland, in which students explore and use abstract concepts concretely [9]. His vision inspired numerous researchers and educators who thought his idea was an “alternative to the prevailing technocentric and behaviorist notions of computer-aided instruction” [10]. Then in 2006, Jeanette Wing originated a discussion about the use of CT across all disciplines. She explored some fundamental questions of what computer science is and how CT could solve human problems. She also argued that including computing into all disciplines allows researchers to uncover new approaches to problem-solving. She defines CT as “solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science” [11]. In 2011, Wing expanded her definition of CT to be "thinking is the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can effectively be carried out by an information-processing agent” [12]. Her definition included smart agents that promote the use of computer science concepts in non-computer science fields. Consequently, CT gained increased attention from the research community, although no unified definition of CT has yet been developed.

Barr and Stephenson asserted that automation could be used to solve problems in a wide range of educational settings. They claimed that CT concepts such as automation, algorithms and procedures, abstraction, problem decomposition, parallelization, simulation, and data (representation, analysis, collection) could supplement and enhance teaching methods [13]. In contrast, Selby and Woollard defined CT concepts as a mental process for problem-solving. The authors considered it to be a cognitive process for humans only, not machines, and their study focused on abstraction, decomposition, algorithmic thinking,
evaluation, and generalization [14]. Brennan and Resnick defined CT from programming contexts, providing an important three-dimensional perspective in terms of CT concepts, CT perspectives, and CT practices. They further categorized CT concepts as semantic, syntactic, and strategic knowledge, while CT practices primarily related to strategic knowledge [15]. Large companies such as Microsoft and Google have also expanded CT applications by facilitating and developing projects using CT in diverse fields [16]. For example, Google designed a CT concept guide that distinguishes mental processes from tangible outcomes. It involves abstraction, algorithms, automation, data collection, data analysis, data representation, decomposition, parallelization, pattern generalization, pattern recognition, and simulation [17]. Based on the above two studies, Weese and Feldhausen, incorporated computer science principles into a preferred CT set [18]. CT lists are shown in generalization. Brennan and Resnick defined CT from programming contexts, providing an important, which we adopted for this paper.

Table 1. Computational Thinking Concepts and Related Computer Science Principles.

<table>
<thead>
<tr>
<th>Abbr.</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG</td>
<td>Algorithmic thinking – the sequence of steps that complete a task. Operators and expressions are also included.</td>
</tr>
<tr>
<td>ABS</td>
<td>Abstraction – generalized representation of a complex problem, ignoring extraneous information.</td>
</tr>
<tr>
<td>DEC</td>
<td>Problem decomposition – breaking a problem into smaller, more manageable parts that can be solved independently of each other.</td>
</tr>
<tr>
<td>DAT</td>
<td>Data – collection, representation, and analysis of data.</td>
</tr>
<tr>
<td>PAR</td>
<td>Parallelization – simultaneous processing of a task.</td>
</tr>
<tr>
<td>CON</td>
<td>Control flow – directs an algorithm’s steps when to complete.</td>
</tr>
<tr>
<td>IAI</td>
<td>Incremental and iterative – building small parts of the program at each step instead of the whole program at once.</td>
</tr>
<tr>
<td>TAD</td>
<td>Testing and Debugging – performing intermediate testing and fixing problems while developing</td>
</tr>
<tr>
<td>QUE</td>
<td>Questioning – working to understand each part of the code instead of using code that is not understood well.</td>
</tr>
<tr>
<td>USE</td>
<td>Reusing and remixing - making use of other people’s work and resources to solve a problem.</td>
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</tbody>
</table>

Chain Association Method

The chain method, or mnemonic link system, is a memorization technique that creates an association between elements in a list. Mnemonic methods manipulate original information into a form the brain can readily process [19]. Several techniques can be used to chain information: The first technique involves memorizing a list, and the second technique involves memorizing a list with associative images. The Von Restorff effect claims that a story with absurd pictures is easier to remember than a story with regular images [20]. Their claim emphasizes that how a connection is built between two elements is more effective and valuable than humorous images. We utilized both techniques to construct the MM.

Mind Maps

Although mind maps and concept maps initially appear similar, they are distinctly different. Concept maps identify relationships between concepts that are typically arranged in boxes or circles that are assembled in a downward hierarchy alongside labeled arrows. Association builds from causes or requirements. A typical concept map example is the Unified Modeling Language (UML). Mind maps, on the other hand, use a centralized idea with branching supporting information [2]. Mind maps are multi-sensory because they utilize colors and pictures. Mind maps date back to the third century when early thinkers and philosophers expressed their thoughts using diagrams. In the late 1970s, Tony Buzan, a British psychology...
Related Work
Only one paper was found that directly addresses CT via concept maps. Weiwei et al. suggested a systematic knowledge growth pattern derived “from problem to problem” to achieve learning outcomes of the curriculum while using the right motivation for students. Students were asked to transform the cognitive structure (course material) into concept maps, and then later, from the concept maps, the instructor identified instructional problems to determine the mastery of student learning outcomes. Students were asked to list all essential information before building relationships between the material and the concept maps [24].

One major difference in the research for this paper was the curriculum layout was replaced with MM to specifically investigate the effect of mind maps on CT skills and how efficiently MM can be incorporated into a curriculum. Weiwei et al. also completed a summative assessment to note improvement, but not to measure the amount of improvement. Conversely, the current study conducted pre-tests and post-tests to determine learning gains, thereby lowering the risk of poor internal validity that could affect students’ results. Furthermore, Weiwei et al. measured student engagement using formative assessment, while the present study used an observation rubric to estimate engagement.

Method
Setting and Sample
Quota sampling (in lieu of random sampling) was performed in a CS0 (introductory computer science) course. This course is designed by instructors to engage students in a variety of topics while reinforcing why computing science is essential. The curriculum replaces routine exams with hands-on interactive activities to encourage discussion and analysis, although some lecture material is used to introduce topics. In addition to in-class activities, this class requires several assignments and group projects outside of class; each student is required to subscribe to TopHat for attendance, lecture questions, discussion, and to help instructors assess and measure student learning and understanding.

A variety of participants were involved (n=80), comprised of 15 female students and 65 male students. Of the total sample, 56% are classified as computer science majors and 44% non-computer science majors. Approximately half of the class was sophomores (51.2%), while 22.5% were seniors, 17.5% were juniors, and 8.8% were freshmen. The course had two sections (A and B) with 40 participants registered in each section where students are not the same in SS and MM. Additionally, a one main instructor, four teaching assistants (two TAs per section) and one observer participated in the experiment. The protocol for this study was approved by university research compliance.

Instruments
Data was collected from the students using student pre-tests and post-tests, clicker-like questions (using TopHat) within the experiments and session recordings for observation. Three instruments were used to measure the study outcomes. Instrument 1 tested students’ learning outcomes using pre-tests and post-tests. Quizzes were assembled from past course exams and similar online courses. Instrument 2 studied students’ self-assessments of CT
concepts using pre- and post-self-efficacy surveys by Weese and Feldhausen [18], containing 10 CT concepts (ALG, CON, DEC, IAI, USE, TAD, DAT, ABS, PAR, QUE). Instrument 3 observed engagement and body language of the instructors and how concepts were delivered through each session. Using a rubric based on Dr. Edward Desmarais’s presentation assessment rubric, using evaluation methods and the nine principles of good practice for assessing student learning [25]

Storyboard-tree
A storyboard tree is a technique to construct a MM by associate information based on a memorable story, promoting retrieval within the flow of a story. The idea of chaining the information as a story adopted from chain association method [2]. Figure 1 presents a high-level overview of the primary application steps for MM: **Pre-Start:** gather all the information in one file to be able to see the mains and supportive ideas. **The first step – the extraction:** identifying, extracting, and listing information, with new information posted under the parent information. This step is repeated until no further information is gained from the reference. The generated list is referred to as a Hierarchy list:

**Example:**
Find main nouns/entities in the information: Interactive Web Page, JavaScript, HTML, CSS, Script.js, Fancy.css, Ticktacktoe.html
Create Hierarchy list (H-List):
Interactive Web Page
---HTML
----Ticktacktoe.html page
---CSS
----Fancy.css file
---JavaScript
----Script.js

Figure 1. Overview of a Storyboard-tree
The second step – the chaining: is chaining, in which a story is created from the H-List. In this step, each sibling should cause retrieval of the next sibling in the same level. This continues with the step1 and step2, but with siblings and their descendants:

Example:
1) Story between sibling: HTML can include CSS file and JavaScript
2) Story between descendant: Interactive web page can be controlled by a JavaScript, like playing a tictacktoe game like script.js code

The third step – the MM creation: the H-List is used to construct the mind map. See Figure 2 below:

The final step- the slide creation: the MM slide is created by deciding on which portion of the MM would be implemented. Images that fit the information are used to connect each point using arrows. See Figure 3b & Figure 3d.

MM Integration
This research utilized two types of materials: theoretical and activities shown in Figure 3. The theoretical materials covered the history of the internet and how the internet works. The activities combined the theoretical and hands-on activities, such build basic websites. Although conversion of theoretical materials occurs naturally, chaining the activities requires more attention, because many indirect links between the information can be influencing. The
understanding and connecting those bonds require experience. Activity slides hold more sequence, so framing the connection to a story was not initially obvious requirement. This study rebuilt it with a similar flow, including an additional point to maintain a logical run and hold the steps. Overall, the method worked efficiently without significant obstacles.

**Design**

The research method of this study followed a quasi-experimental design since the students were not randomly selected and not randomly divided. We consider each section as a group, Section A was the control group with the classic layout, and Section B was the research group with mind map slides. The research was carried out over a two-week period with a total of four sessions (each lasting 75 minutes). The coursework and assignments were identical and mandatory for both sections according to course requirements. Part of the course requirement is answering course knowledge questions using TopHat during each lecture. The answers measured students’ understanding over the course, similarly to what the post-test does. Thus, we utilized the post-test incrementally every lecture replacing questions in TopHat with a portion of the post-test. By doing so, we reduce the load where students won’t have to take it twice. Qualitative methods were also employed. Each classroom session was observed and recorded to analyze classroom interactions.

Before the experiment, students completed a questionnaire about CT and a pre-test over course knowledge to reduce internal validity threats of students remembering pre-test questions. The first two sessions covered the history of the internet and how the internet works. The last two sessions were a combination of theoretical instruction, such as HTML, web servers, web 2.0 technologies, and hands-on activities, such as students learning how to connect and communicate with the Linux server to build basic websites. During the last week of this research, students were asked to develop a website using what they learned about basic HTML, JavaScript, and CSS. A week later, students submitted their projects online and answered the post-survey.

**Results**

This study analyzes answers and interactions of students to measure the effect of mind maps on the curriculum, thus, considering the following research questions:

- **RQ1** Does using this method affect a student’s CT skills?
- **RQ2** Does using this method affect students’ knowledge?
- **RQ3** Instructor preference?

In the analysis of survey results, we calculated descriptive statistics and two-way ANOVA considering the teaching method, student major and university level. The teaching method has two groups mind maps group (MM) and the classic group (SS). Major is divided into computer science students (CS) and non-computer science students (Non-CS). University levels are split into freshmen (F), sophomore (So), junior (Ju) and senior students (Se).

Out of a total sample size of 80 students, students who did not complete the surveys or quizzes were partially excluded. As an example, if a student only participated in some of the surveys, their answers will be used only in those survey data sets. However, if the student answered all surveys or quizzes questions, he or she will be included in all datasets. We constructed two main datasets from answers of the instruments where each set has its categories: **1) Computational thinking set (CT)** (n=52): has students’ scores over the 10 CT concepts: (ALG, CON, DEC, IAI, USE, TAD, DAT, ABS, PAR, QUE). **2) Course knowledge set (CK)** (n=49): has the difference scores between student’s pre-test and post-test.
In Figures 4 and 5 significant results are shaded based on associated p-values. An asterisk designated improved performance due to MM with an indicator from the Bonferroni test and underlined for MM without the Bonferroni significant indicator. The effect size following eta-squared $\eta^2 = \frac{SS_{effect}}{SS_{total}}$ is noted as a small, moderate, and large reference; bold font indicates a large effect (.14), italicized indicates medium effect (.06) and no marks indicate a small (.01).

Does using this method affect a student’s CT skills?

Figure 4 shows that the method on its own did not statistically alter students' self-efficiency scores, even though ABS and QUE have better means in the MM section with large p-values (> .05), which indicates weak evidence. For the (method and university level), the effect size almost doubled compared to the (method) but was not statistically significant. The ALG concept in (method and university level) showed statistically significant differences between MM-freshmen and SS-freshmen, the MM group demonstrating better results. Similarly, the full interaction (method, major, and university level) indicated a significant difference between MM and SS students with $F(1,38) = 6.34, p = .016, \eta^2 = .07$. Bonferroni test confirms that the higher scores between CS freshmen and non-CS freshmen in MM group ($M = 0.0, SD = 0$) than the control group ($M = -1.75, SD = 0$). The PAR and QUE concepts violated the homogeneity assumption when the method interacted with the university level. Therefore, the university level was excluded from ANOVA tests for these two. The
remaining CT concepts have different trends where all the underlined values are a better performance to the MM method but not confirmed by P-values (P > 0.51). Hence, we can imply that MM can be a promising method to improve learning CT.

The mean scores of CT concepts in Figure 4 were shown to be negative, which could potentially highlight student seriousness and/or confidence in answering the pre/post-tests. Thus, Table 2 provided more investigation on how students’ self-judgments changed by examining the difference between pre-test and post-tests. In other words, students are categorized based on the percentage of changing the answers; the changes measured by subtracting the post-test selections from the pre-test. Students divided according to the difference between three quantiles (30%, 60%, and 90%). If the difference is two or less (e.g., change the selection from 4 to 2, or 3 to 1) for most of the questions, he/she falls in 30% quantile. The second quantile has a difference by 3 (e.g., change from 5 to 2). The last row has a difference of 4. The first row shows that 92% of students change their opinion slightly, and 8% of the students their confidence increased/dropped. We suspect the course load is the reason behind the change where students must submit a project, labs and complete surveys in two weeks. Table 3. Percentage of students’ self-judgment investigated students’ self-judgments, it presents percentages of student self-judgment by comparing survey CT scores to their project CT scores. The difference can be either Miss, Fair, or Good. "Fair" judgment has a +/− 1 difference between self-efficacy score and project score (“miss” with -2 to “good” with +2). Results showed that student confidence dropped by 36.5% for “miss” judgments and 31% of students did not consider themselves improved, which is a fair assessment since some students may have already had this knowledge. However, 35% of students with “good” judgments saw improvement in themselves.

### Table 2. Percentage of changing answer with at least two levels between pre-post tests

<table>
<thead>
<tr>
<th>Changing Answer Ratio</th>
<th>Students Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%-30%</td>
<td>92%</td>
</tr>
<tr>
<td>30%-60%</td>
<td>7.7%</td>
</tr>
<tr>
<td>60%-90%</td>
<td>0%</td>
</tr>
</tbody>
</table>

### Table 3. Percentage of students’ self-judgment on Computational Thinking

<table>
<thead>
<tr>
<th>Judgments</th>
<th>MM</th>
<th>SS</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miss</td>
<td>35.7%</td>
<td>37.5%</td>
<td>36.5%</td>
</tr>
<tr>
<td>Fair</td>
<td>28.6%</td>
<td>33.3%</td>
<td>30.8%</td>
</tr>
<tr>
<td>Good</td>
<td>35.7%</td>
<td>33.3%</td>
<td>34.6%</td>
</tr>
</tbody>
</table>

**Instructor preference**

The results statistically prove that the instructor’s preferences for the SS method as a teaching technique to deliver course outcomes. The SS group indicate a higher rating (M = 4.30, SD = .333) than the MM group (M = 3.2, SD = .826). Class observation is used to explore the cause behind the instructor’s preference. The instructor body language revealed that the instructor had more positive reactions toward the SS method, potentially due to a lack of experience since the MM method was integrated and implemented quickly with limited time to practice. Also, the instructor was more experienced in traditional teaching methods, so the instructions were less smoothly delivered during the MM method because of the unfamiliarity of the flow. In addition, the instructor has to teach both methods in one day.

**Does using this method affect students’ knowledge?**

Figure 5 shows similar knowledge gained between the mind map group and the classic group means (F(1, 37) = .058, p = .811, η2 = 0.001) and all interactions were not significant. MM-non-CS has the best performance yield, with a mean of 6.08, compared to MM-CS (3.3), SS-
Distribution and scatter plots for course knowledge score in Figure 6 show unequal whisker lengths for CS and non-CS in SS. The first quartile’s scores indicate significant distribution, and the third quartile’s scores show a high level of agreement. The MM-non-CS boxplot is comparatively different than the other plots, potentially indicating that non-CS students interacted positively with this method with a high level of agreement between scores.

A further investigation to see if students' academic performance through the course affecting their opinion. We developed three models using hierarchical multiple regression on student academic performance and their fondness of the majors. The regression was calculated to predict student fondness based on course knowledge scores above and beyond their methods and majors. Results showed that neither the first model (course knowledge score variables only) nor the second model (knowledge scores plus majors) nor the third model (knowledge scores, majors, and method) predicted fondness scores to a statistically significant degree: Model1: F(1,35) = .20, p = .652, η² = 0.005; Model2: F(2,34) = 1.05. and Model3: F(2,38) = 0.721. Thus, course knowledge is not a factor in predicting fondness.

Limitation
Validity is a concern with the post-test. Instructors measured student engagement and understanding of the course materials via clicker questions - multiple questions answered by clicking on the choice, using an interactive application, where responses and results automatically collected and tabulates. This study divided the post-test into four smaller tests
to avoid overwhelming students with multiple repetitious questions. The questions were offered as clicker questions in each class. However, the structure between the pre-test and post-test will be different. The research hypothesis claimed that providing corresponding questions after the relative instruction still accurately measures a change in knowledge. Leading pre-test and post-test designs, such as classic post-test design, post-test-only design, time-series design, and retrospective design, all include a post-test after the intervention. Some alternative measuring designs, which use percentages instead of pre-tests and post-tests, also record data after the intervention.

Because the Storyboard-tree cannot account for all MM methods, and no recent study has distinguished the difference between a traditional mind map and a chain mind map, this study can only generalize as to the effectiveness of MM incorporation into similar domains. In addition, the method did not allow enough time for instructors and students to practice, so students had trouble taking notes since the slides contained many unfamiliar arrows and figures. MM creation was based only on the Storyboard technique, not the instructor’s usual method of creating their course materials; the thing that might have a different teaching flow of the course. The instructor might not have been comfortable when using the produced slides, leading to unintentional insincerity when delivering the course.

Conclusions
Computational thinking has been gaining worldwide attention as a 21st-century learning skill. Substantial research has focused on curriculum creation and integration of CT, but little on the method of integration. This pilot study examined the use and effectiveness of MM as a teaching strategy for CT. We developed the Storyboard-tree technique to transform traditional slides (SS) into the MM structure. The applied materials are models in an introductory CS course, where the course utilizes two sections: one taught with MM, and the other with SS. The observed academic results, CT self-efficiency scores, and the acceptance rate were encouraging. Data was collected incrementally through classroom observation and pre/post-tests of the students. The data shows that two-thirds of the students confer seriousness/fairness in answering the tests. The findings of the MM method, though not conclusive, show that MM freshman self-efficiency scores are higher than the SS class in the algorithm concept. Most of the CT concepts confer notable performance to the MM section but were not statistically supported. The top academic performance went to non-CS students in the MM section; the remaining groups showed a comparable trend. Both methods hold a close rating for efficacy among students. Still, we cannot predict the growth of students' knowledge, depending on their fondness scores. The overall findings present the MM method as a feasible way to deliver CT concepts, making it a possible strategy to support learning CT.

References
[29] U. Wisconsin, best practices and course evaluations surveys.