MINING, ANALYZING, AND MODELING THE COGNITIVE STRATEGIES STUDENTS USE TO CONSTRUCT HIGHER QUALITY CAUSAL MAPS

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ABSTRACT

The Jeong (2020) study found that greater use of backward and depth-first processing was associated with higher scores on students' argument maps and that analysis of only the first five nodes students placed in their maps predicted map scores. This study utilized the jMAP tool and algorithms developed in the Jeong (2020) study to determine if the same processes produce higher-quality causal maps. This study analyzed the first five nodes that students (n = 37) placed in their causal maps to reveal that: 1) use of backward, forward, breadth-first, and depth-first processing produced maps of similar quality; and 2) backward processing had three times more impact on maps scores than depth-first processing to suggest that linking events into chains using backward chaining is one approach to constructing higher quality causal maps. These findings are compared with prior research findings and discussed in terms of noted differences in the task demands of constructing argument versus causal maps to gain insights into why, how, and when specific processes/strategies can be applied to create higher-quality causal maps and argument maps. These insights provide guidance on ways to develop diagramming and analytic tools that automate, analyze, and provide real-time support to improve the quality of students' maps, learning, understanding, and problem-solving skills.

KEYWORDS

Critical Thinking, Knowledge Maps, Learning Analytics

1. INTRODUCTION

A variety of computer-aided diagramming tools are available or in development for creating argument, causal, and concept maps that are being used in education to visualize relationships and evaluate complex ideas (Giabbanelli, Tawfik, & Wang, 2023). These diagramming tools are used to create argument maps to visualize and identify hierarchical relationships between premises and claims to evaluate the structural soundness of complex arguments (Braak et al., 2006; Davies, Barnett, & van Gelder, 2019; Davies, 2011), causal maps to examine relationships between networks of variables/events and outcomes to reveal causal explanations (Desthieux, Joerin, & Lebreton, 2010; McCrudden, Schraw, & Lehman, 2009), and concept maps to examine relationships between concepts or ideas with labeled links that indicate the nature of the relationships (Cañas, Novak, & Reiska, 2015). These tools have been found to improve learning and critical thinking skills with moderate to large effect sizes (Schroeder, Nesbit, Anguiano, & Adesope, 2017; Eftekhari, Sotoudehnama, & Marandi, 2016; Harrell, 2011; van Gelder, 2015; Yue, Zhang, Zhang, & Jin, 2017), and reduce cognitive load by making relationships more concrete and facilitating analysis (Novak & Cañas, 2007). However, there can still be a high degree of variance in map quality, even when interventions are used to achieve significant gains in map quality (Ruiz-Primo & Shavelson, 1996).

Constructing maps can be a complex and challenging process even with the help of computer-aided diagramming tools (Beitz, 1998; Cañas, Reiska, & Möllits, 2017; Kinchin, 2001). As a result, specific mapping strategies examined and prescribed in the research literature include directing students to place the goal at the top (Eppler, 2006), sorting before linking nodes (Aguiar & Correia, 2017), sorting nodes by level of generality (Cañas, Reiska, & Möllits, 2017), positioning nodes with reading flow or temporal flow (Aguiar & Correia, 2017; Jeong & Lee, 2012), using five whys with backward chaining, goal-oriented, and depth-first process (Al-Ajlan, 2015; Chen, Li, & Shady, 2010; Sharma, Tiwari, & Kelkar, 2012), and using a breadth-first process to review maps (Biswas, Segedy, & Bunchongchit, 2016). Maps can be classified by structure and different learning approaches and outcomes are associated with them (He et al., 2023; Kinchin, 2011). Spokes often contain static linking phrases that result in restricted insights, and chains suggest rote learning when node sequences may be resistant to change. In contrast, networks are linked with meaningful learning when nodes are connected with dynamic explanatory phrases and cycles indicate iterative learning processes.

Currently, only a limited number of studies have been conducted to identify, validate, and model the cognitive strategies students use to construct maps. A more in-depth and precise analysis of the specific processes utilized by students can assist researchers in determining to what extent specific strategies are used by students to construct maps (Wang, 2019), help determine whether the utilization of specific strategies results in higher quality maps (Schroeder, Nesbit, Anguiano, & Adesope, 2017), better understand how specific characteristics of mapping tools and learner attributes influence what processes students use, and how mapping tools can be designed to more effectively monitor and provide real-time guidance on what strategies to use.

Two case studies investigated the cognitive strategies used by students when constructing argument maps (Jeong & Kim, 2022) and causal maps (Lee, 2012). Using verbal protocol analysis, Jeong and Kim (2022) found that both experts and novices used more breadth-first (BR) processing than depth-first (D) processing when constructing *argument* maps. More breadth-first processing was also found to be associated with higher quality *causal* maps (Shin & Jeong, 2021). Depth-first (Figure 1 left) is performed when the placement of 1 is followed by the placement of 2 immediately below 1. Breadth-first (Figure 1 right) occurs when the placement of 1 is followed by the placement of 2 to the immediate right or left of 1 (at the same level). Jeong & Kim (2022) also found that four of the five experts used more backward (B) than forward (F) processing to construct argument maps, when one novice used more backward process and the other four novices used a mix of backward and forward processing. The backward or deductive process is performed (Figure 1 left) when the placement of 1 is followed by the placement of 2 immediately below 1. The forward process (or inductive process) occurs when the placement of 3 is followed by the placement of 2 immediately above 3. Use of backward processing has also been found to be associated with higher quality causal maps (Lee, 2012; Shin & Jeong, 2021).

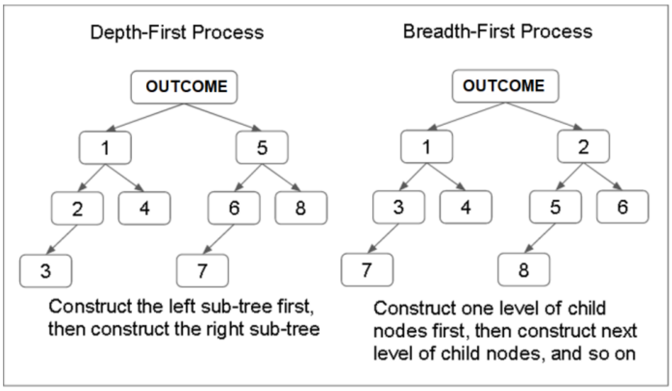


Figure 1. Illustration of the depth-first and breadth-first process

To analyze larger samples of maps with greater precision, the placement of nodes in relation to previously moved nodes can be used to automate map assessments (Taricani & Clariana, 2006) and identify the processes used by students in constructing a map (Jeong, 2020). Jeong (2020) developed the jMAP tool to log the on-screen actions of students while constructing *argument* maps. The tool used an algorithm to analyze the log data and measure the frequency of backward, forward, breadth-first, and depth-first processing performed by students. This study found that: 1) analyzing the placement of only the first five nodes moved on screen (not 10, 20 or all moved nodes) produced backward/forward and breadth/depth-first process ratio scores that were significant predictors of map scores; 2) greater use of *backward* and *depth-first* processing were used to produce better argument maps; and 3) simple observed frequencies of backward and depth-first processing alone (not ratio scores) were not found to be significant predictors of argument map scores. The analysis of simple frequencies instead of ratio scores and small sample size in the Jeong & Kim's (2022) case study help to explain why they found breadth-first processing (not depth-first processing) to be associated with higher quality argument maps.

The purpose of this study was to determine which of the four processes (backward, forward, breadth-first, depth-first) create higher quality causal maps. The same tools and metrics used by Jeong (2020) to identify the processes that create better argument maps were employed in this study. Argument maps are created by students when asked to evaluate the strength and validity of an argument by identifying the premises presented to support the argument and the logical relationships between premises. On the other hand, causal maps are created when students are asked to identify the critical variables/events and causal pathways that contribute to a specific outcome. These differences in task demands suggest that the processes used to create better argument maps may not necessarily create better causal maps. As a result, this study aimed to address the following research questions:

1. Does greater use of backward over forward processing produce better causal maps?
2. Does greater use of breadth-first over depth-first processing produce better causal maps?
3. Which process (backward versus breadth-first) has a greater impact on scores?

2. METHOD

2.1 Participants

The participants were 43 students (21 females, 22 males) at a large southeastern university. Six of the participants were undergraduates enrolled in a research subject pool and 37 were graduate students recruited via leaflets and received $15 gift certificates for participating. The students were informed that the student that created the highest-scoring causal map receives an additional $10 gift certificate. After reviewing and signing an IRB-approved consent form to participate in this study, the students' demographic information was collected using a brief survey. The survey was used to identify which if any participants had prior knowledge of causal maps, how to construct them, or any prior experience using causal mapping tools. No participants had prior knowledge and experience with using causal maps.

2.2 Procedure

The students viewed a video introduction to the jMAP software (Jeong, 2018) with demonstrations on how to drag and re-position nodes in the map, insert links to chain causally related variables (A→B = A affects B), and change the color of links (with red indicating an inverse relationship). Each student opened a jMAP file on a laboratory desktop computer with blank nodes that students used to practice moving and inserting links between nodes. Next, students received a handout initially placed face down with definitions of the outcome and each variable presented in the map nodes. The students were then instructed to start working on the causal map by clicking on a button to turn on a screen recorder, flipping over the handout to view the instructions and node definitions, and opening the jMAP file to view the initial screen (Figure 2) containing the outcome variable positioned to the far right and all variables positioned randomly on the left. The students were given a maximum of 15 minutes to complete their map. The average completion time was 9.79 minutes.

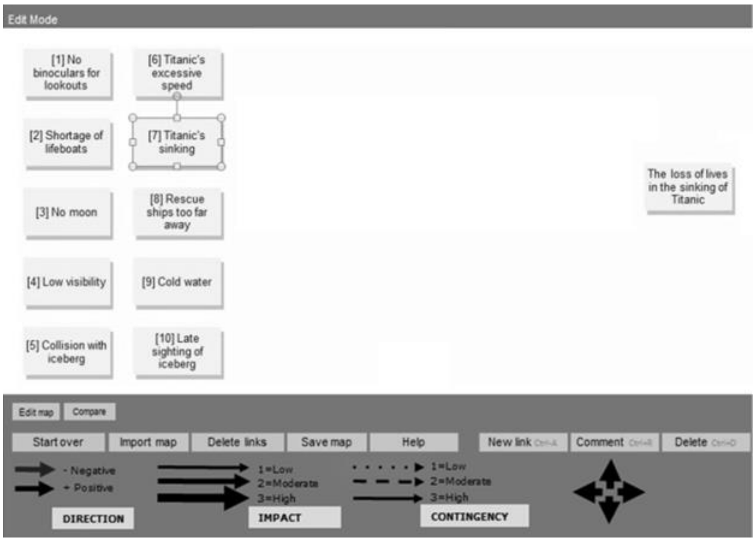
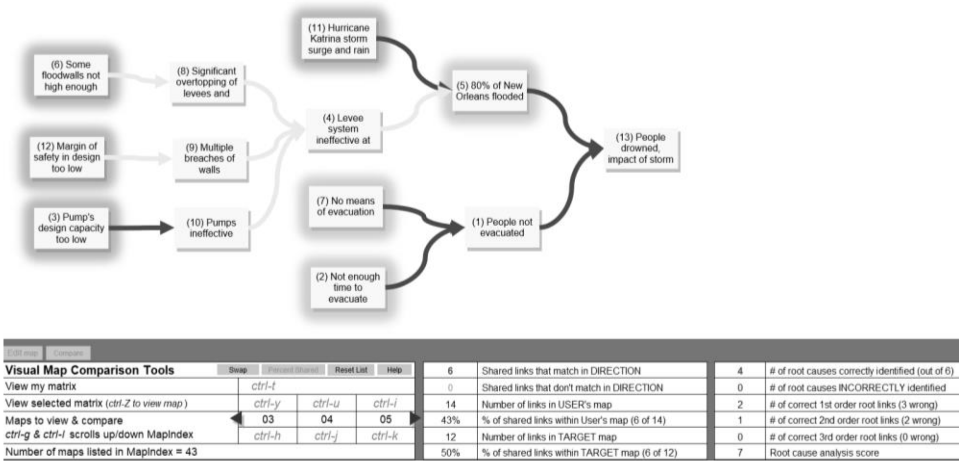


Figure 2. Example screen with events/conditions positioned and linked to produce the criterion causal map

2.3 Data Analysis

Of the 42 student maps, 37 maps were scored and analyzed in this study. Five maps created in a spoke structure were removed from analysis because identifying which processes were during the construction of spoke-like map is unreliable and problematic. The 37 maps were imported into jMAP and were compared to the criterion map (Figure 3) to score each student's map on five criteria: a) percentage of links within the student's map that match those in the criterion map; b) number of nodes correctly identified as a root premise; c) number of 1st order premises correctly linked from each correctly identified root premise; d) number of 2nd order premises correctly linked from each 1st order premise; and e) number of 3rd order premises correctly linked from each 2nd order premise. No points were awarded for 2nd and 3rd order links if downstream link(s) are missing. The first two criteria were used to measure causal understanding, and the last three criteria were used to measure depth of understanding. The total points received across all six criteria were added up, and then multiplied by 10 to compute each student's map score. The maximum possible score was 340 and mean score was 126.95 (*STD* = 55.47, *n* = 37) or 43.69% of the total possible score.



Note: Black/gray arrows identify links present/missing in student x's map; Nodes with halos demark correctly identified root causes; bottom left are navigation tools to select which maps to compare with criterion map; bottom right displays map scores across scoring criteria; bottom row displays the buttons students used to add links to their maps.

Figure 3. Visual and quantitative comparison of the criterion to student's map in jMAP

Each time a node was placed on screen, jMAP assigned the action with a code (Table 1) identifying where the node was placed in relation to the previously moved node (e.g., MDn = moved different node north of previously moved node). These codes were analyzed using an algorithm developed by Jeong (2020) to determine what processes students were using to construct their maps based only on the first five nodes placed on screen. The algorithm identified the position of a placed node relative to the position of the previously moved node to identify a backward (B), forward (F), breadth-first (BR), depth-first (D) process. For example, placing B to the left of outcome node C followed by placing A to the left of B (moving from right to left) was coded as backward processing. Conversely, placing event A to the left of C and placing B between A and C was coded as forward processing.

Table 1. Codes logged following each node placement in jMAP during map construction

Code	Definition
MS	moved a node (which was the same node as the last moved node)
MDn	moved node to the North of the previously moved node
MDs	moved node to the South of the previously moved node
MDe	moved node to the East of the previously moved node
MDw	moved node to the West of the previously moved node
MDne	moved node to the NE of the previously moved node
MDnw	moved node to the NW of the previously moved node
MDse	moved node to the SE of the previously moved node
MDsw	moved node to the SW of the previously moved node

Forward and backward processing served as behavioral indicators of depth-first processing as nodes are placed sequentially moving towards or away from the outcome. The placement of B immediately above or below A (with both A and B at approximately equal distance from the outcome) indicates breadth-first processing. Because the algorithm cannot infer what processes are used when creating spoke-like maps, five maps were removed, leaving a total of 37 causal maps used in the analysis.

The observed frequencies for B, F, BR, and D were used to compute two ratio scores: BF = B/(B+F) and BRD = BR/(BR+D). Both measure the extent to which students used backward over forward processing and breadth-first over depth-first processing. The association between ratio scores and map scores were then tested using the regression model **Map Score** = **B0** + **B1***BF + **B2***BRD using a one-tailed *p*-value of .10 to conduct this exploratory study. These results were then compared with the model and findings from Jeong's (2020) study on the processes used to create higher quality argument maps.

3. RESULTS

The two process scores and map scores produced the best-fit model **Map Score** = **117.84** + **52.06***BF - **16.81***BRD with $F(2, 34) = .790$, $p = .461$. The process scores were *not* found to be predictors of students' causal map scores. Individually, the BF scores ($M = .31$, $STD = .23$, $n = 37$) was a non-significant predictor of causal map quality at $p = .109$, with 33% of the students using backward processing equal to or greater than the number of times they used forward processing in their first five moves. The BRD scores ($M = .48$, $STD = .26$, $n = 37$) was a non-significant predictor at $p = .324$, with 51% of students using breadth-first processing equal to or greater than the number of times they used depth-first processing in their first five moves. The model explained little of the variance in students' map scores, with $R2 = .044$.

These results show that the use of either backward or forward processing can produce causal maps of similar quality. Similarly, the use of either breadth-first or depth-first processing can produce causal maps of similar quality. The model indicates that students' choice in using backward vs. forward processing had three times more impact on map scores than their choice in using breadth- vs. depth-first processing.

4. DISCUSSION

4.1 Processes Associated with Map Scores

The findings indicate that use of any of the four processes can produce causal maps of similar quality. This finding differs from the Jeong (2020) study where more use of backward processing and more use of depth-first processes was associated with higher quality argument maps. Some possible explanations for these differences in findings may be that events in causal maps are generally more concrete and easier to comprehend than premises presented as more abstract ideas. As a result, a distant link A-C in a causal map may be just as easy to recognize as more proximal links A-B and B-C that form the chain A-B-C (due to the concrete nature of events and human propensity for predicting future events as an evolutionary survival skill). This can make it easier to link events into the correct pathway using any of the four processes. In contrast, the logical but distant link from premise A to premise C may not be as easy to discern (perhaps due to higher levels of abstraction and specificity) until A is linked to B-C to complete the A-B-C chain. This type of process would require students to rely more on using a systematic chaining process (using depth-first and backward processing) as the findings suggest in Jeong's (2020) study of argument mapping processes.

4.2 Processes used to Construct Causal Maps

These findings suggest that the use of any of these four processes produces causal maps of similar quality when in contrast, Jeong (2020) found that greater use of backward and depth-first processing produces higher quality argument maps. The findings in this study also show that more use of backward processing is positively associated with the quality of causal maps, consistent with the findings from prior studies with causal maps (Lee, 2012) and argument maps (Jeong, 2020; Jeong & Kim, 2022). This finding is also consistent with the findings and conclusions of other studies supporting the use of backward processing over forward processing (Al-Ajlan, 2015; Chen, Li, & Shady, 2010; Sharma, Tiwari, & Kelkar, 2012). The one exception as to when forward processing might be preferable to learners (but not necessarily the most effective) is when a particular topic is highly complex and/or unfamiliar (Al-Ajlan, 2015).

The model indicates that higher use of depth-first processing relative to the use of breadth-first processing can be (but not necessarily) positively associated with higher quality causal maps. This finding is consistent with Jeong's (2020) findings on the processes used to produce better argument maps. However, Shin & Jeong (2021) found that more use of breadth-first (not depth-first processing) was associated with better causal maps. One explanation for the differences in findings is that Shin & Jeong (2021) conducted a regression analysis using *all* the actions (including map revision) students performed up to the time they completed their causal maps (not just the placement of the first five nodes). As a result, the model produced by Shin & Jeong (2021) and the resulting findings may not be an accurate or reliable measure of the specific processes students used to construct better causal maps.

Finally, the model suggests that students' choice in using backward versus forward processing can (but not necessarily) have three times more impact on causal map quality than students' choice in using breadth-first versus depth-first processing. Jeong (2020) found that these two process choices had nearly equal impact on the quality of argument maps. This difference in finding could be (as discussed above) attributed to how recognizing distant links between events in *causal* maps may be easier than recognizing distance links between premises in argument maps. If this is the case, the findings in this study suggest that the students' showed a propensity to work immediately and specifically on linking events into chains (using backward chaining and doing it with temporal flow) instead of using a breadth-first process to sort events by level of generality and reduce the complexity of the mapping task at the start of the activity.

4.3 Future Research

Although the findings suggest that using any of the four processes can produce causal maps of the same quality, replicating this study with a larger sample size and with more complex topics might reveal possible associations between processes and map quality. Future studies can compare processes used to construct causal versus argument maps (and other types of maps) in controlled experiments by presenting the same outcome/topic (to control for topic complexity and familiarity) to students in a causal mapping group and to students in an argument mapping group. The causal mapping group can be instructed to identify the pathways that lead to outcome X while the argument mapping group can be instructed to analyze the validity and veracity behind the proposition that argues for and predicts the same outcome X used with argument maps. In the meantime, the number of given events for the causal map should be kept equal to the number of given premises in the argument map. The complexity of the topic can be steadily increased to see if the degree of reliance on using specific processes change.

To examine the impact of use of breadth- vs. depth-first processing, use criterion maps with a larger number of branches given that this and the Jeong (2020) study used criterion maps with only two main branches. Differences between the breadth versus depth of the criterion map may affect the probability in which students perform a depth-first action over a breadth-first action in the first five moves based on chance alone (not based on their choice of cognitive strategy). In addition, BRD scores can be computed iteratively in relation to expected scores to account for increases/decreases in the likelihood of selecting and placing a low- or high-level node based on what remaining nodes are waiting to be placed in the map. Nevertheless, testing the best-fit model using *ratio* scores accounts for how often each student uses a breadth-first process over depth-first process *relative* to how many times other students use it when testing for associations between process and map scores (regardless of how the number of nodes at the highest level affect the likelihood of performing breadth-first processing).

5. CONCLUSION

This study used the methods developed by Jeong (2020) - previously employed to examine argument mapping processes - to identify the processes students use to construct better causal maps. This study's findings suggest that all four processes (backward, forward, breadth-first, and depth-first) can be used to create causal maps of comparable quality. The analysis of this study's findings and noted differences in the task demands associated with the construction of causal maps versus argument maps provide insights into key considerations to keep in mind when selecting appropriate strategies for constructing causal and argument maps. These insights provide directions for future research aimed at creating more advanced mapping tools to analyze and support student strategies in real-time and measure its impact on map quality. By testing the efficacy of different mapping strategies using new and improved mapping tools, we can work systematically on increasing and reducing the variance often seen in the quality of students' maps to improve student learning, understanding, and problem-solving.

REFERENCES

Aguiar, J. G., & Correia, P. R. M., 2017. From representing to modelling knowledge: Proposing a two-step training for excellence in concept mapping. *Knowledge Management & E-Learning*, Vol. *9*, No. 3, pp. 366–379.

Al-Ajlan, A., 2015. The comparison between forward and backward chaining. *International Journal of Machine Learning and Computing*, Vol. 5, No. 2, p. 106.

Beitz, J. M., 1998. Concept mapping: Navigating the learning process. *Nurse Educator*, Vol. 23, No. 5, pp. 35–41.

Biswas, G., Segedy, J. R., & Bunchongchit, K., 2016. From design to implementation to practice a learning by teaching system: Betty's Brain. *International Journal of Artificial Intelligence in Education*, Vol. 26, No. 1, pp. 350–364.

Braak, S. W. van den., Oostendorp, H. van., Prakken, H., & Vreeswijk, G. A., 2006. A critical review of argument visualization tools: Do users become better reasoners? In F. Grasso, R. Kibble, & C. A. Reed (Eds.), Workshop Notes of the ECAI-2006 Workshop on Computational Models of Natural Argument (pp. 67-75). Riva del Garda:Italy.

Cañas, A. J., Novak, J. D., & Reiska, P., 2015. How good is my concept map? Am I a good Cmapper? *Knowledge Management & E-Learning*, Vol. 7, No. 1, pp. 6-19.

Cañas, A. J., Reiska, P., & Möllits, A., 2017. Developing higher-order thinking skills with concept mapping: A case of pedagogic frailty. *Knowledge Management & E-Learning*, Vol. 9, No. 3, pp. 348–365.

Chen, J. C., Li, Y., & Shady, B. D., 2010. From value stream mapping toward a lean/sigma continuous improvement process: An industrial case study. *International Journal of Production Research*, Vol. 48, No. 4, pp. 1069–1086.

Davies, M., 2011. Concept mapping, mind mapping and argument mapping: what are the differences and do they matter? *Higher Education*, Vol. 62, No. 3) pp. 279-301.

Davies, M., Barnett, A., & van Gelder, T., 2019. Using computer-assisted argument mapping to teach reasoning to students. In J. A. Blair (Ed.), *Studies in critical thinking* (Vol. 8, pp. 131–176). Windsor, Canada: Windsor Studies in Argumentation.

Desthieux, G., Joerin, F., & Lebreton, M., 2010. Ulysse:A qualitative tool for eliciting mental models of complex systems. *System Dynamics Review*, Vol. 26, No. 2, pp. 163-192.

Eftekhari, M., Sotoudehnama, E., & Marandi, S. S., 2016. Computer-aided argument mapping in an EFL setting: Does technology precede traditional paper and pencil approach in developing critical thinking? *Educational Technology Research and Development*, Vol. 64, No. 2, pp. 339-357.

Eppler, M. J., 2006. A comparison between concept maps, mind maps, conceptual diagrams, and visual metaphors as complementary tools for knowledge construction and sharing. *Information Visualization*, Vol. *5*, No. 3, pp. 202–210.

Giabbanelli, P. J., Tawfik, A. A., & Wang, B., 2023. Designing the next generation of map assessment systems: Open questions and opportunities to automatically assess a student's knowledge as a map. *Journal of Research on Technology in Education*, Vol. 55, No. 1, pp. 79-93.

Green, N., 2017. Argumentation scheme-based argument generation to support feedback in educational argument modeling systems. *International Journal of Artificial Intelligence in Education*, Vol. 27, No. 3, pp. 515-533.

Harrell, M., 2011. Argument diagramming and critical thinking in introductory philosophy. *Higher Education Research & Development*, Vol. 30, No. 3, pp. 371-385.

He, X., Fang, J., Cheng, H. N., Men, Q., & Li, Y. (2023). Investigating online learners' knowledge structure patterns by concept maps: A clustering analysis approach. *Education and Information Technologies*, pp. 1-22.

Jeong, A. C., & Lee, W. J., 2012. Developing causal understanding with causal maps: The impact of total links, temporal flow, and lateral position of outcome nodes. *Educational Technology Research & Development*, Vol. 60, pp. 325–340.

Jeong, A. C., 2020. Developing computer-aided diagramming tools to mine, model and support students' reasoning processes. *Educational Technology Research and Development*, Vol. 68, pp. 3353-3369.

Jeong, A., & Kim, H. Y., 2022. Identifying critical thinking skills used by experts versus novices to construct argument maps in a computer-aided mapping tool. *Knowledge Management & E-Learning*, Vol. 14, No. 2, pp. 125-149.

Jeong, A., 2018. jMAP. Last retrieved on April 26, 2023 at http://bit.ly/causalmaps.

Kinchin, I. M., 2001. If concept mapping is so helpful to learning biology, why aren't we all doing it? International *Journal of Science Education*, Vol. 23, No. 12, pp. 1257–1269.

Kinchin, I. M., 2011. Relating knowledge structures to learning styles and university teaching. In *Style Differences in Cognition, Learning, and Management*, Edited by: Rayner, S. and Cools, E. Pp. 129–142. Routledge.

Lee, W.J., 2012. Exploring students' mapping behaviors and interactive discourses in a case diagnosis problem: Sequential analysis of collaborative causal map drawing processes (Unpublished dissertation). Florida State University, Tallahassee, FL.

McCrudden, M. T., Schraw, G., & Lehman, S., 2009. The use of adjunct displays to facilitate comprehension of causal relationships in expository text. *Instructional Science*, Vol. 37, No. 1, pp. 65-86.

Moore, T., 2004. The critical thinking debate: How general are general thinking skills? *Higher Education Research & Developmen*, Vol. 23, No. 1, pp. 3–18.

Novak, J., & Cañas, A., 2007. Theoretical origins of concept maps, how to construct them, and uses in education. *Reflecting Education*, Vol. 3, No. 1, pp. 29-42.

Ruiz-Primo, M., & Shavelson, R., 1996. Problems and issues in the use of concept maps in science assessment. *Journal of Research in Science Teaching*, Vol. 33, No. 6, pp. 569-600.

Schroeder, N., Nesbit, J., Anguiano, C., & Adesope, O., 2017. Studying and constructing concept maps: A meta-analysis. *Educational Psychology Review*, Vol. 30, No. 2, pp. 431–455.

Sharma, T., Tiwari, N., & Kelkar, D., 2012. Study of difference between forward and backward reasoning. International *Journal of Emerging Technology and Advanced Engineering*, Vol. 2, No. 10, pp. 271–273.

Shin, H. S., & Jeong, A., 2021. Modeling the relationship between students' prior knowledge, causal reasoning processes, and quality of causal maps. *Computers & Education*, Vol. 163, 104113.

Taricani, E., & Clariana, R., 2006. A technique for automatically scoring open-ended concept maps. *Educational Technology Research and Development*, Vol. 54, No. 1, pp. 65–82.

van Gelder, T., 2015. Using argument mapping to improve critical thinking skills. In M. Davies & R. Barnett (Eds.) *The Palgrave handbook of critical thinking in higher education* (pp. 183-192). Palgrave Macmillan, London.

Wang, S., 2019. *Providing intelligent and adaptive support in concept map-based learning environments*. Doctoral dissertation, Arizona State University, USA.

Yue, M., Zhang, M., Zhang, C., & Jin, C., 2017. The effectiveness of concept mapping on development of critical thinking in nursing education: A systematic review and meta-analysis. *Nurse Education Today*, Vol. 52, pp. 87–94.