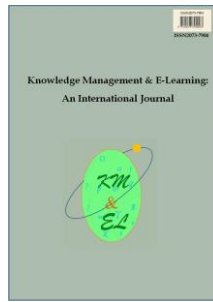

Mining and modelling the cognitive strategies students use to construct higher quality causal maps

Allan Jeong

Florida State University, USA

Hyoung Seok Shin

Chungbuk National University, Korea



Knowledge Management & E-Learning: An International Journal (KM&EL)
ISSN 2073-7904

Recommended citation:

Jeong, A., & Shin, H. S. (2026). Mining and modelling the cognitive strategies students use to construct higher quality causal maps. *Knowledge Management & E-Learning*, 18(3), 430–445.
<https://doi.org/10.34105/j.kmel.2026.18.019>

Mining and modelling the cognitive strategies students use to construct higher quality causal maps

Allan Jeong* 

Anne Spencer Daves College of Education
Florida State University, USA
E-mail: ajeong@fsu.edu

Hyoung Seok Shin 

College of Medicine
Chungbuk National University, Korea
E-mail: shin.hyoungseok@gmail.com

*Corresponding author

Abstract: This study examines the cognitive strategies students employ when constructing causal maps and investigates whether specific processing methods — backward versus forward and breadth-first versus depth-first — affect map quality. Building on prior research that linked backward and depth-first processing to stronger argument maps, the study applied similar analytical tools to causal mapping, a task with distinct cognitive demands. Using jMAP software, 37 causal maps were created by students at a Southeastern university in the United States. Within the first five nodes placed, students used backward, forward, breadth-first, and depth-first processing an average of 0.81, 1.84, 1.73, and 1.95 times, respectively, producing maps with a mean score of 125.82 (SD = 55.13) out of a possible 340. Regression analysis revealed that neither backward nor breadth-first processing significantly predicted map scores, though a non-significant trend suggested that more frequent backward processing may support higher-quality maps, consistent with prior findings on argument mapping. While not definitive, these results carry instructional implications: encouraging backward processing and designing diagramming tools that facilitate this strategy without inadvertently biasing students toward less effective approaches. Ultimately, the study highlights that predominant reliance on forward, backward, or breadth-first processing does not necessarily yield higher-quality causal maps as it does in argument mapping, underscoring the importance of understanding task-specific demands to inform instructional design and the development of tools that better support student reasoning and problem-solving.

Keywords: Cognitive strategies; Causal maps; Learning analytics

Biographical notes: Dr. Allan Jeong is an Associate Professor of Instructional Systems and Learning Technologies at Florida State University. His research focuses on critical thinking and problem-solving, with an emphasis on developing learning analytics tools that visually model online discourse and reveal the strategies students use to construct causal and argument diagrams.

Dr. Hyoung Seok Shin is a research scientist in medical education, evaluating medical students' performance to conduct research and provide instructional consultation to improve medical students' competencies, problem-solving skills,

and reasoning processes.

1. Introduction

A variety of computer-aided diagramming tools are used by students to create causal maps, which enable them to visualize relationships and evaluate complex ideas (Davies et al., 2021; Giabbanelli et al., 2023). Students can create causal maps to examine relationships between networks of variables and events and reveal causal explanations (Desthieux et al., 2010; McCrudden et al., 2009). These tools help to reduce cognitive load by making possible relationships more concrete and easier to explore (Novak & Cañas, 2007), thus leading to improvements in learning (Cañas et al., 2023) with moderate to large effect sizes (Schroeder et al., 2018; Eftekhari et al., 2016; Harrell, 2011; van Gelder, 2015; Yue et al., 2017), and possible improvements in students' critical thinking skills (Barta et al., 2022; Fonseca et al., 2024). However, even when interventions are used to achieve significant gains in map quality, a high degree of variance in map quality can still be observed (Ruiz-Primo & Shavelson, 1996). Prior research on the effects of mapping on the development of students' critical thinking skills has also yielded highly mixed results, as diagramming tools lack the means to identify, measure, and verify the processes students use while constructing their maps (Jeong et al., 2025).

Constructing maps can be a complex and challenging process even with the help of computer-aided diagramming tools (Beitz, 1998; Cañas et al., 2003; 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 et al., 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 et al., 2010; Sharma et al., 2012), and using a breadth-first process to review maps (Biswas et al., 2016). Maps can be classified by structure, and different learning approaches and outcomes are associated with them (He et al., 2023; Kinchin, 2011). For example, constructing maps with temporal flow (organized sequentially from left to right, from top to bottom, or vice versa) tends to result in higher quality maps (Jeong & Lee, 2012). In contrast, spokes-like maps lack temporal flow and are of lower quality.

Currently, few studies explore, validate, or model the cognitive strategies students use to create maps. For example, Jeong et al.'s (2025) review of 17 studies that examined how concept mapping affects students' critical thinking skills (e.g., deduction, induction, inferencing, evaluation) found that the results were highly mixed and inconsistent, with less than half of the studies reporting positive and significant gains in students' critical thinking skills. Concept maps are graphical tools that represent knowledge structures by linking concepts with labelled connections; these links specify semantic or causal relationships, making abstract ideas more explicit and easier to analyse. None of the studies measured the specific critical thinking skills students used while constructing concept maps or how those processes affected map quality. A more comprehensive and precise examination of the specific techniques employed by students can help assess the extent to which these strategies are utilized. This analysis can also shed light on whether

the application of these strategies leads to the creation of higher-quality maps (Schroeder et al., 2018; Wang, 2019). Moreover, this research can provide insights into how specific features of mapping tools and individual student attributes influence the choice of strategies, as well as how mapping tools can be designed to effectively monitor and offer real-time guidance on strategy selection.

Two case studies examined the cognitive strategies students used when constructing argument maps (Jeong & Kim, 2022) and causal maps (Lee, 2012). Argument maps represent logical relationships among claims and evidence, while causal maps emphasize cause-and-effect pathways. Using verbal protocol analysis, Jeong & Kim (2022) found that both experts and novices favoured breadth-first (BR) over depth-first (D) processing when building argument maps with the conclusion at the top. Breadth-first processing (placing nodes above or below one another), as illustrated in the right causal map in Fig. 1, was also linked to higher-quality causal maps (Shin & Jeong, 2021), whereas depth-first involves elaborating horizontally along a single branch (e.g., the left causal map in Fig. 1). They also reported that four of five experts used more backward (B) than forward (F) processing, while novices showed mixed patterns. Backward processing (placing nodes to the left of prior ones) reflects deductive reasoning, whereas forward processing (placing nodes to the right) reflects inductive reasoning. Prior studies have likewise associated backward processing with stronger causal maps (Lee, 2012; Shin & Jeong, 2021).

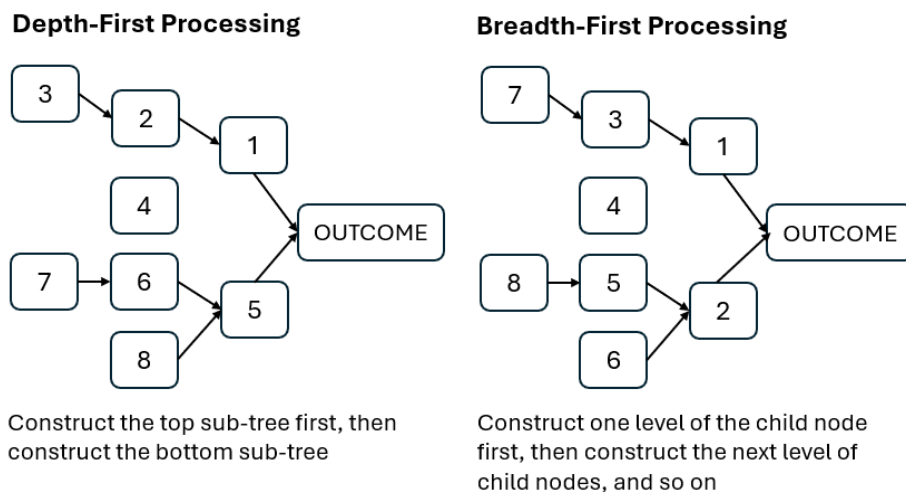


Fig. 1. Illustration of the depth-first and breadth-first processes (note: the numbers indicate the order in which nodes are placed on the map)

The findings in the two prior case studies were derived from qualitative examination of a limited number of student-generated maps. To analyse larger sets of maps and gain deeper insights into the processes involved in their creation, automated analysis methods can be employed. One such method is to examine the placement of nodes in relation to previously placed nodes to determine the strategies students use to construct their maps (Taricani & Clariana, 2006). Importantly, analysing the positioning of only the first five nodes placed on the screen before students move or re-position nodes provides a clearer window into their spontaneous cognitive strategies. These initial placements capture raw decision-making rather than later adjustments. They reduce the

noise introduced by trial-and-error corrections or surface-level refinements (e.g., spacing between nodes). They also ensure comparability across maps of different sizes. Finally, they highlight the critical stage of map construction when organizational patterns like temporal flow (Jeong & Kuba, 2023) are first established. Building on this approach, Jeong (2020) developed and used the jMAP tool to record students' actions while constructing maps and applied an algorithm to count the number of times students used backward, forward, breadth-first, and depth-first processing based on the placement of each node relative to the previously moved node. Notably, regression analysis tests conducted in the study showed that analysing the first 10, 15, and all placed nodes did not significantly predict map scores, reinforcing the importance of focusing on the first five node placements as the most reliable indicator of students' mapping strategies.

The Jeong (2020) study revealed several important findings. Ratio scores (reflecting the balance between backward/forward and breadth/depth-first processes) derived from the first five node placements significantly predicted the quality of students' argument maps. This means that the way students initially approached the task, whether they tended to look backward to connect new ideas to earlier ones, or forward to extend their maps into new territory, had measurable consequences for the overall strength of their arguments. Similarly, the preference for depth-first processing, in which students elaborated on a single branch of reasoning before moving on, was linked to more coherent and well-developed maps compared to breadth-first processing, which spreads attention across multiple branches without fully developing any one of them. These findings suggest that early cognitive strategies are not just momentary choices but set the foundation for the logical structure and persuasiveness of the entire map. In contrast, simple frequency counts of backward and depth-first processing, rather than ratio scores, were not significant predictors of argument map scores. This distinction highlights that the relative balance of strategies is more meaningful than raw totals, since it reflects how students coordinate different approaches rather than how often they use them in isolation. Taken together, the results underscore the importance of examining the nuanced interplay of mapping strategies in the earliest stages of construction, as these initial decisions appear to shape the quality of the final product.

However, this particular study (Jeong, 2020) explored the strategies students used when constructing argument maps rather than causal maps. Students were given in advance a specific claim or conclusion along with a list of major and minor premises to analyse and organize into an argument map. The students were instructed to visually link the given claims, evidence, and counterarguments into a structured format to clarify their logical relationships. In contrast, causal maps depict cause-and-effect relationships between events or variables, showing how one element influences another, often with feedback loops and dynamic interactions. While both tools use nodes and connections to represent relationships, argument maps focus on logical reasoning and debate, whereas causal maps emphasize system behaviour and interdependencies. Additionally, the study noted that placing a node below or above a previously moved node reflected backward or forward processing, respectively, because the main claim in students' argument maps was placed at the top of the map. Understanding these mapping techniques is essential, as they highlight distinct cognitive strategies students use to analyse information either through logical argumentation or causal reasoning.

This study aimed to explore whether higher ratios of backward processing over forward processing, and depth-first over breadth-first processing, can also enhance students' ability to construct better causal maps, not just argument maps. On one hand,

argument maps are crafted by students as they identify the premises put forth to support the argument, which is inherently a process of working backwards from the argument. In contrast, causal maps come into being as students identify the pivotal variables and events and the causal pathways that contribute to a given outcome. Identifying causal pathways can involve the use of a backward process to identify the causal pathways – a process that is most efficient for diagnosing complex problems (Al-Ajlan, 2015). At the same time, identifying causal pathways can also involve using a chronological moving-forward-in-time process – a process that is more innate in human nature (Sweller et al., 2011; Tversky & Kahneman, 1977), as it mirrors how humans naturally learn from and make predictions within their environment as a survival mechanism. Consequently, using forward processing precludes the use of breadth-first processing as defined in the Jeong (2020) study because the exploration of the possible outcomes following and branching from each specific event (building tree structures) is not relevant to the task of identifying the chain of events that lead to an already-specified target outcome (building inverted tree structures).

These noted disparities in the task demands imply that the processes conducive to constructing superior argument maps may not necessarily yield improved causal maps. As a result, this study aimed to address the following research questions.

RQ1: Does more frequent use of backward over forward processing produce better causal maps?

RQ2: Does more frequent use of breadth-first over depth-first processing produce better causal maps?

RQ3: Which process (backward versus breadth-first) has a greater impact on scores?

2. Method

2.1. Participants

The participants were 42 students (20 females, 22 males) at a large southeastern university in the United States who were enrolled in a research subject pool and/or recruited via leaflets and received \$15 gift certificates for participating. The students were informed that the student who 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 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

Students viewed a video introduction to the jMAP software (Jeong, 2025), demonstrating how to move nodes, insert causal links ($A \rightarrow B$), and change link colours to indicate positive or inverse relationships. Each student opened a jMAP file on a laboratory computer containing blank nodes for practice in moving and linking. 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 (Fig. 2) containing the outcome variable positioned to the far right and all variables positioned randomly on the left. Students clicked the Record button so that each action during map construction was logged into an Excel spreadsheet. The students were given a maximum of 15 minutes to complete their map. The average completion time was 9.79 minutes.

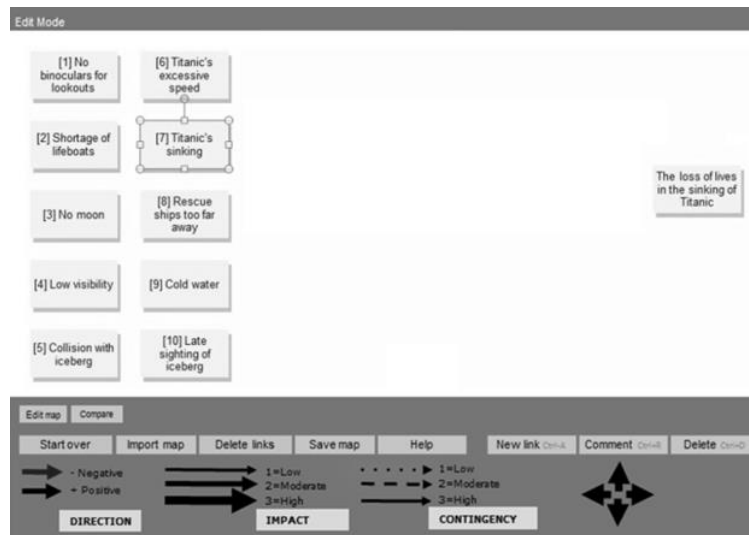


Fig. 2. Example screen with events/conditions positioned and linked to produce the criterion causal map

While students constructed their causal maps, each time a node was placed into their causal map on the jMAP screen, jMAP assigned the action with a code (see Table 1) to record the specific action, and identified where the node was placed in relation to the most recently and previously moved node (e.g., MDn = moved different node north of previously moved node). For instance, in a causal map where the final outcome is placed at the far right edge of the map, placing a node to the immediate right of the previous and most recently placed node (within a -45° to $+45^\circ$ angle) indicated the use of forward processing, while placing the node to the immediate left indicated the use of backward processing. Placing the node immediately above or below the previously placed node (also within -45° and $+45^\circ$) suggested the use of breadth-first processing. Jeong (2020) further refined the accuracy of this coding process by testing and varying the minimum required distance (from 2 to 11 node lengths) between the positioned node and the previously positioned node, ultimately setting the minimum required distance at 1.5 times the width of the nodes.

2.3. Data analysis

Of the 42 causal maps collected in this study, a total of 37 maps were scored and analysed. One causal map was not completed or recorded due to student error. Five maps were created using a spoke-like structure (where the final outcome is placed in the centre of the map) and were excluded from the analysis because the software code at its current state could not clearly and reliably determine when a placed node was an indication of

backward or forward processing. The remaining 37 maps were imported into jMAP where each student's map was compared to the criterion map (see Fig. 3) to automate the scoring of each student's map across 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 with the maximum possible score of 340.

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
MDn	Moved node to the NW of the previously moved node
MDse	Moved node to the SE of the previously moved node
MDs	Moved node to the SW of the previously moved node

To measure how often each student used the backward, forward, and breadth-first processes, the software code developed in Microsoft Excel VBA by Jeong (2020) was used to compute backward/forward and breadth/depth ratio scores from each student's jMAP log. Each log was analysed using the software code to determine the frequencies with which each process (forward, backward, breadth-first) was used while constructing each map based only on the first five nodes placed on screen. As explained previously, the software code analysed the node coordinates recorded in the log to determine the position of each placed node relative to the previously moved node, thereby identifying backward, forward, and breadth-first processing. 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. Forward and backward processing are two forms of depth-first processing (in which 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) indicated the use of breadth-first processing.

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 use backward over forward processing and breadth-first over depth-first processing. The association between ratio scores and map scores was then tested using the regression model $\text{Map Score} = B0 + B1 \times BF + B2 \times BRD$ 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 that identified the processes used to create higher-quality argument maps. The map scores, BF ratio scores, and BRD ratio scores showed no skewness at .00, a weak positive skewness at .37, and a weak positive skewness of .35, respectively. As a result, the BF and BRD ratio scores were transformed by taking the square root of the scores prior to running the regression analysis. No multicollinearity was found as all VIF values were less than 2.5.

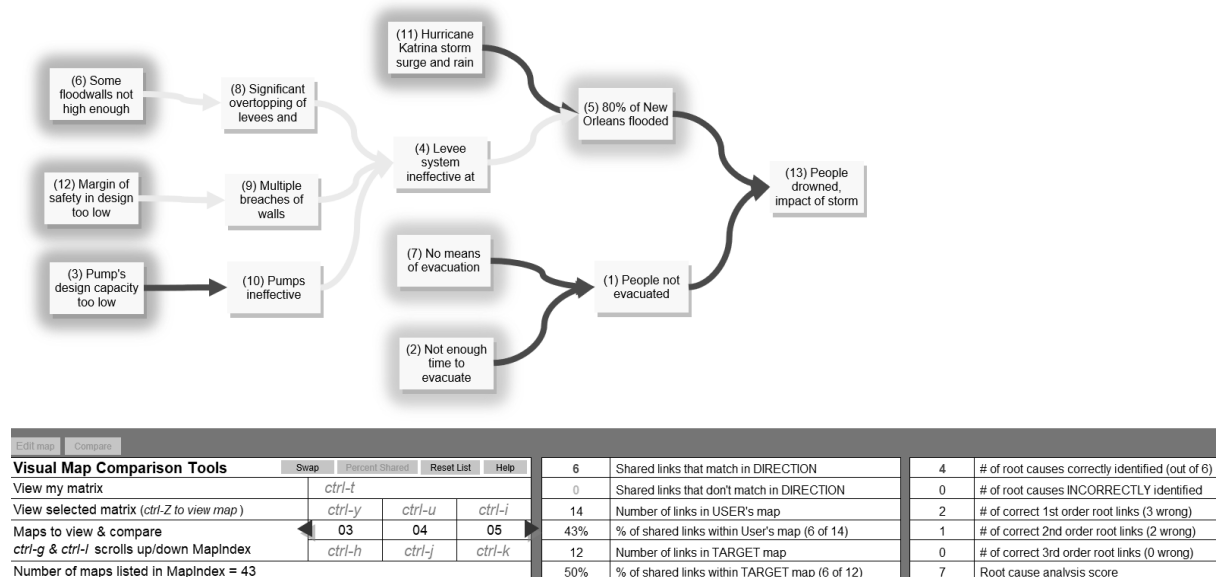


Fig. 3. Visual and quantitative comparison of the criterion to a student's map in jMAP (note: black/grey arrows identify links present/missing in student *x*'s map; nodes with halos demark correctly identified root causes; bottom left are navigation tools to select which maps to compare with the criterion map; bottom right displays map scores across scoring criteria; bottom row displays the buttons students used to add links to their maps)

3. Results

Table 2 shows the mean number of times students used the backward process ($M = .81$, $STD = .57$, $\min = 0$, $\max = 2$), forward process ($M = .81$, $STD = .57$, $\min = 0$, $\max = 2$), breadth-first ($M = .81$, $STD = .57$, $\min = 0$, $\max = 2$), and depth-first ($M = .81$, $STD = .57$, $\min = 0$, $\max = 2$) in the first five nodes students placed into their causal maps. As a result, the minimum and maximum possible number of times students can perform each process was 0 and 5, respectively. The table also shows students' map scores ($M = 125.82$, $STD = 55.13$, $\min = 30.00$, $\max = 250.91$), where the overall mean map score of 125.82 was 37% of the total possible map score of 340.

A significant difference was found between the number of times each student used backward ($M = 0.81$, $SD = 0.57$) versus forward processing ($M = 1.84$, $SD = 0.80$), $t(36) = -6.36$, $p < .001$, paired sample $t(36) = 5.72$, $p < .001$, with a large effect size, $d = -0.94$. Students used forward processing more often than backward processing when placing the first five nodes into their causal maps. No significant difference was found

between the number of times students used breadth-first processing ($M = 1.73$, $SD = 0.87$) versus depth-first processing ($M = 1.95$, $SD = 1.08$), $t(36) = -0.83$, $p = .412$, with a small effect size, $d = -0.14$. As a result, students showed no tendency to use either breadth-first or depth-first process during the initial process of constructing their causal maps.

Table 2

Statistics on the observed mapping behavior and map quality ($N = 37$)

Indicator	Mean	SD	Min	Max
Backward links	0.81	0.57	0	2
Forward links	1.84	0.8	0	3
Backward-forward ratio	0.31	0.23	0	1
Breadth	1.73	0.87	0	3
Depth	1.95	1.08	0	4
Breadth-depth ratio	0.48	0.26	0	1
Map score	125.82	55.13	30	250.91

BF refers to the backward vs. forward ratio, and BRD refers to the breadth vs. depth-first ratio. This two process scores (BF and BRD ratios) and map scores produced the best-fit regression model, $\text{Map Score} = 117.84 + 52.06 \times \text{BF} - 16.81 \times \text{BRD}$, with $F(1, 35) = 1.40$, $p = .244$. The resulting model indicated that BF ($p = .218$) and BRD ($p = .649$) were not significant predictors of map scores, and the model explained 4% of the variance in students' map scores, with $R^2 = .04$. Removing the predictor variable with the highest p -value (BRD ratio) from the analysis produced the model $\text{Map Score} = 111.50 + 46.55 \times \text{BF}$, where BF was again not found to be a significant predictor of map scores ($p = .244$). This result indicates that neither backward vs. forward nor breadth-first vs. depth-first processing significantly affected causal map quality. Although not significant, beta weights reveal two trends suggesting that using more backward than forward processing and more depth-first than breadth-first processing produced higher-quality causal maps. Assumption checks indicated that residuals were normally distributed (Shapiro-Wilk $p = .959$), with no concerns regarding multicollinearity ($\text{VIFs} < 2.5$). The White test revealed heteroscedasticity ($F = 193.04$). As a result, the coefficient estimates may be inefficient and associated with inflated standard errors.

The overall model indicated that neither predictor reached statistical significance, though the coefficients suggested different directional trends. The BF ratio was positively associated with map scores ($B = 52.06$, $p = .218$), indicating that greater reliance on backward relative to forward processing tended to predict higher scores, but the effect was small and not definitive. Its partial η^2 value (.044) reflected a small effect size, accounting for about 4% of the variance uniquely explained. In contrast, the BRD ratio showed a negative, nonsignificant association with map scores ($B = -16.81$, $p = .649$), with a negligible partial η^2 (.006). Taken together, these findings suggest that while backward processing may show a weak trend toward improving causal map quality, neither BF nor BRD ratios contributed meaningfully to explaining differences in students' map scores.

4. Discussion

4.1. Processes associated with causal map scores

This study demonstrated that the primary processing strategies students employed, whether forward, backward, or breadth-first, did not exert a statistically significant influence on the quality of the causal maps they produced. In practical terms, students generated causal maps of comparably low quality regardless of the strategy applied. This finding stands in contrast to Jeong (2020), who reported that higher-quality argument maps were significantly associated with backward and depth-first processing. A plausible explanation for this divergence lies in the differing cognitive demands of the two tasks: constructing argument maps versus constructing causal maps. In causal mapping, forward processing may be less detrimental than in argument mapping because causal maps often follow a temporal or chronological sequence, thereby rendering forward processing relatively more effective. This helps to explain why students in this study used forward processing significantly more often than backward processing (despite the data trends that suggest that using backward processing is more effective). By contrast, argument maps typically involve propositions that are not temporally interrelated, which may explain why forward processing is less advantageous in that context. The absence of differences between breadth-first and depth-first approaches may likewise reflect the structural constraints of the causal mapping task. Because students were asked to connect events to a predetermined outcome, they had little need to identify multiple causes for a single event. Instead, the task encouraged an inverted tree structure, making both breadth-first and depth-first strategies equally viable.

Furthermore, events in causal maps are typically more concrete (and not just temporally anchored), which makes them easier to comprehend than the abstract, context-sensitive premises found in argument maps. This concreteness may enable students to identify distant causal links (e.g., $A \rightarrow C$) as readily as more immediate ones (e.g., $A \rightarrow B$ and $B \rightarrow C$), thereby facilitating the construction of accurate pathways through either forward or backward processing. In contrast, the logical relationships among abstract premises in argument maps are often less transparent. For example, the connection between premise A and premise C may only become evident once the intermediate link $A \rightarrow B$ has been established, forming a complete $A \rightarrow B \rightarrow C$ reasoning chain. This added complexity increases cognitive demands and likely prompts students to adopt more deliberate and structured strategies, such as depth-first and backward processing, to ensure that their argument maps are coherent and logically sound.

Although the regression model was not significant, the beta weights in the model revealed a potential trend: how often students used backward instead of forward processing appeared to have roughly twice the impact on causal map quality compared to how often students used breadth-first over depth-first processing. This contrasts with Jeong (2020), where both types of processing choices had a similar effect on the quality of argument maps. This potential difference (though not definitive) in findings may stem once again from differences in the nature of causal mapping tasks. Causal maps involve concrete events, making distant connections easier to identify when using either forward or backward processing. For these reasons, students may rely less on using the breadth-first approach to conduct a preliminary sorting of like-events as described by Cañas et al. (2017) – a strategy that can be used to manage cognitive load and task complexity (Al-Ajlan, 2015). However, this noted difference in the relative impact of using depth-first

versus breadth-first processing could also be the product of structural differences (e.g., number of branches relative to the length of the branches) between the target causal maps examined in this study and the argument maps examined in the Jeong (2020) study where the criterion argument map had higher numbers of branches than the criterion causal map used in this study. As a result, future comparisons of breadth/depth-first processing ratios in causal versus argument mapping will need to be conducted under more controlled conditions.

Taken together, these findings suggest that the relationship between processing strategies and map quality may be task-dependent, with argument mapping requiring more deliberate structuring than causal mapping. Prior studies of argument maps (Jeong, 2020; Taricani & Clariana, 2006) consistently reported that backward and depth-first processing were linked to stronger map quality, likely because these strategies support the logical chaining of abstract premises and the careful development of reasoning pathways. In contrast, the current study found no significant differences in causal map quality based on processing strategy, indicating that the concreteness and temporal sequencing of causal tasks may reduce the need for such deliberate structuring. This divergence highlights an important distinction: while argument maps benefit from strategies that emphasize coherence and logical depth, causal maps appear to allow students to achieve similar outcomes through a wider range of approaches.

Finally, the findings reveal a trend where students who rely more on backward processing than on forward processing produce higher-quality causal maps. Forward processing often leads to causal chains that resemble temporal or narrative sequences, such as “*Victims fell into the water*”, “*The water was deep*”, and “*Victims lost their lives*”. While this sequence follows a chronological storyline, the first two events are independent, and the causal connections are weak or misleading. In contrast, backward processing prompts students to interrogate causal relationships more critically by working backward from the outcome and asking questions like “*Did victims die because the water was deep?*” (yes) or “*Was the water deep because the victims fell into the water?*” (no). This reflective reasoning enables them to test the plausibility of causal links, uncover inconsistencies, and avoid the common error of confusing temporal sequence with causation. As a result, students who adopt backward processing may be more likely to detect logical fallacies more effectively and demonstrate deeper analytical reasoning, producing causal maps that more accurately represent underlying mechanisms rather than superficial event order.

4.2. Instructional implications

Taken together, the findings and the distinctive characteristics of causal mapping yield several pedagogical implications for fostering higher-quality student work. In particular, instructional guidance may emphasize the utility of backward rather than forward chaining when students are tasked with linking and explaining the events that culminate in a specified outcome, a recommendation consistent with practices in argument mapping. At the same time, it is crucial to acknowledge that the way instructors model the causal mapping process can inadvertently favour one strategy over another. For example, repeatedly demonstrating either forward or backward chaining may lead students to infer that the modelled approach represents the preferred or normative method, thereby discouraging the adoption of potentially more effective alternatives such as backward processing. To mitigate this risk, instructors should deliberately present, contrast, and validate proven strategies during instruction, making explicit the conditions under which

each approach is most effective. Such intentional modelling not only broadens students' strategic repertoire but also reinforces backward processing as a particularly valuable tool for constructing coherent and logically sound causal maps.

Likewise, computer-based diagramming tools can be intentionally designed to facilitate greater use of backward processing. For instance, to support backward chaining, students could be provided with the option to select node B, which would display " $\rightarrow B$ " on screen (corresponding to statements such as "*B is caused by ...*" or "*B occurs because...*"), and then drag and drop node A to the left of B to form the $A \rightarrow B$ link. Although such backward linking functionality is rarely incorporated into existing diagramming platforms, adding such a function as a default setting in a diagramming tool could significantly increase the likelihood of students using backward processing more than forward processing. At the same time, in circumstances where forward processing may be more effective, tools can be designed to encourage forward processing by allowing students to select node A, which would display " $A \rightarrow$ " on screen (corresponding to statements such as "*A causes ...*"), and then drag and drop node B onto A to complete the $A \rightarrow B$ link. Perhaps it will be possible in the future to create diagramming tools that can detect the most appropriate times to apply one approach over another to help students construct higher-quality maps.

Finally, diagramming tools could be intentionally designed to prompt students to identify the target outcome at the outset of the mapping session and, by default, position that outcome at the top of the workspace. Such a layout affords students greater opportunity to employ both backward and forward processing, thereby supporting the construction of causal maps in an inverted-tree structure. In contrast, when students are permitted to place the outcome freely, some may elect to position it centrally, as observed in 5 of the 42 students in this study, resulting in spoke-like configurations. These spoke-like layouts can hinder the intentional application of backward and forward processing and disrupt the temporal flow of causal reasoning. Moreover, they complicate the ability of tools such as jMAP, or future diagramming systems, to detect whether students are engaging in backward or forward processing, to evaluate the reasoning processes underlying their maps, and to deliver targeted prompts that scaffold their thinking. By guiding students to begin with a clearly positioned outcome and structuring the interface to reinforce directional processing, software tools can more effectively facilitate the production of high-quality causal maps and enable more accurate analyses of complex problems.

4.3. Study limitations and future research

The results indicate that the mapping processes examined in this study did not definitively enhance the quality of students' causal maps. Overall scores were relatively low, with the average map score only 37% of the maximum possible. Larger sample sizes are needed to determine if greater use of backward and depth-first processing can significantly improve map quality. Future studies can also vary task design, such as specifying or leaving nodes open in advance, and employing more complex subjects to uncover links between map quality and other processes not yet identified and measured using the methods described in this study. Research can also compare how causal and argument maps are constructed under controlled conditions, balancing factors such as prior knowledge, number of nodes, and sub-trees. One approach is to present both groups with the same subject matter to reduce differences in topic complexity and familiarity. For example, causal mapping participants could trace pathways leading to a specific

outcome (X), while argument mapping participants could evaluate the strength and truthfulness of claims about outcome X. To ensure consistency, the number of events in causal maps can be matched with the number of premises in argument maps. Researchers may also increase topic complexity gradually to observe whether students rely more heavily on certain cognitive processes as tasks become more demanding.

In this study, five causal maps with a spoke-like configuration were excluded because the computer code developed by Jeong (2020) could not reliably determine whether students were using forward or backward reasoning based on node placement. Kinchin (2011) notes that spoke-like structures often rely on static linking phrases, which restrict deeper understanding, and once connections are made, students are less likely to revise them. This suggests that students who create spoke-like maps may produce lower-quality causal maps. Including these maps in future analyses could reveal how and when specific strategies help students construct stronger causal maps. To support this, the computer code can be refined to identify forward processing when a node is placed between the previously moved node and the final outcome, and backward processing when the previously placed node lies between the newly placed node and the final outcome. The code and analytic algorithms can also be enhanced to analyse and identify possible processes students are using the moment they link two events in a causal map.

To examine the impact of using breadth- vs. depth-first processing, further studies can be conducted using 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 can affect the probability with which students perform a depth-first action over a breadth-first action in their first five moves based on chance alone (not based on their choice of cognitive strategy). At the same time, BRD ratio scores can be computed iteratively in relation to expected scores to account for increases/decreases in the likelihood of selecting a sibling node among the number of remaining nodes that have yet to be positioned and placed in the map.

4.4. Conclusion

This study employed the tools and methods developed by Jeong (2020), originally designed to analyse argument maps, to investigate the processes students use when constructing causal maps. The findings, although not conclusive, suggest that backward processing can help students create higher-quality maps, similar to the results found in argument mapping. In contrast, greater use of depth-first processes did not appear to improve map quality. These differences from prior studies on argument maps (Jeong, 2020) may reflect the distinct task demands of causal versus argument mapping, highlighting the need for strategy-specific guidance. In addition to these findings, this study demonstrates some possible approaches to designing future computer-aided diagramming tools to support students' reasoning in real-time and measure the impact of specific processes on learning outcomes. This is particularly relevant given that prior research on mapping and critical thinking has produced mixed results, largely because researchers lack the means to measure and verify the processes students use as they construct maps. By refining these tools, future research can be directed towards the creation of automated diagramming tools, combined with the use of generative AI, that can identify what strategies students are using to help them build more effective maps in the process of strengthening their reasoning, understanding, and problem-solving skills.

Author Statement

The authors declare that there is no conflict of interest.

ORCID

Allan Jeong  <https://orcid.org/0000-0001-5797-3223>

Hyoung Seok Shin  <https://orcid.org/0000-0002-7785-4755>

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*, 9(3), 366–379. <https://doi.org/10.34105/j.kmel.2017.09.022>
- Al-Ajlan, A. (2015). The comparison between forward and backward chaining. *International Journal of Machine Learning and Computing*, 5(2), 106–113. <https://doi.org/10.7763/IJMLC.2015.V5.492>
- Barta, A., Fodor, L. A., Tamas, B., & Szamoskozi, I. (2022). The development of students' critical thinking abilities and dispositions through the concept mapping learning method – A meta-analysis. *Educational Research Review*, 37: 100481. <https://doi.org/10.1016/j.edurev.2022.100481>
- Beitz, J. M. (1998). Concept mapping: Navigating the learning process. *Nurse Educator*, 23(5), 35–41. <https://doi.org/10.1097/00006223-199809000-00015>
- 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*, 26(1), 350–364. <https://doi.org/10.1007/s40593-015-0057-9>
- Cañas, A. J., Coffey, J. W., Carnot, M. J., Feltovich, P., Hoffman, R. R., Feltovich, J., & Novak, J. D. (2003). *A summary of literature pertaining to the use of concept mapping techniques and technologies for education and performance support*. The Institute for Human and Machine Cognition. Retrieved from <https://www.ihmc.us/users/acanas/Publications/ConceptMapLitReview/IHMC%20Literature%20Review%20on%20Concept%20Mapping.pdf>
- 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*, 9(3), 348–365. <https://doi.org/10.34105/j.kmel.2017.09.021>
- Cañas, A. J., Reiska, P., & Shvaikovsky, O. (2023). Improving learning and understanding through concept mapping. *Knowledge Management & E-Learning*, 15(3), 369–380. <https://doi.org/10.34105/j.kmel.2023.15.021>
- 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*, 48(4), 1069–1086. <https://doi.org/10.1080/00207540802484911>
- Davies, M., Barnett, A., & van Gelder, T. (2021). Using computer-assisted argument mapping to teach reasoning to students. In J. A. Blair (Ed.), *The Critical Thinking Anthology* (pp. 115–152). 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*, 26(2), 163–192.

- <https://doi.org/10.1002/sdr.434>
- 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*, 64, 339–357. <https://doi.org/10.1007/s11423-016-9431-z>
- 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*, 5(3), 202–210. <https://doi.org/10.1057/palgrave.ivs.9500131>
- Fonseca, M., Marvão, P., Oliveira, B., Heleno, B., Carreiro-Martins, P., Neuparth, N., & Rendas, A. (2024). The effectiveness of concept mapping as a tool for developing critical thinking in undergraduate medical education – A BEME systematic review: BEME guide No. 81. *Medical Teacher*, 46(9), 1120–1133. <https://doi.org/10.1080/0142159X.2023.2281248>
- 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*, 55(1), 79–93. <https://doi.org/10.1080/15391523.2022.2119449>
- Harrell, M. (2011). Argument diagramming and critical thinking in introductory philosophy. *Higher Education Research & Development*, 30(3), 371–385. <https://doi.org/10.1080/07294360.2010.502559>
- He, X., Fang, J., Cheng, H. N. H., Men, Q., & Li, Y. (2023). Investigating online learners' knowledge structure patterns by concept maps: A clustering analysis approach. *Education and Information Technologies*, 28, 11401–11422. <https://doi.org/10.1007/s10639-023-11633-8>
- Jeong, A., & 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 and Development*, 60, 325–340. <https://doi.org/10.1007/s11423-011-9227-0>
- Jeong, A. C. (2020). Developing computer-aided diagramming tools to mine, model and support students' reasoning processes. *Educational Technology Research and Development*, 68, 3353–3369. <https://doi.org/10.1007/s11423-020-09826-w>
- Jeong, A., & Kim, H. Y. (2022). Identifying and linking critical thinking skills used in computer-aided mapping tools to construct argument maps. *Knowledge Management & E-Learning*, 14(2), 125–149. <https://doi.org/10.34105/j.kmel.2022.14.008>
- Jeong, A., & Kuba, R. (2023). Analyzing the syntax and salience of causal links embedded within semantic links in concept maps: Implications for temporal flow and learning transfer. *Knowledge Management & E-Learning*, 15(3), 420–432. <https://doi.org/10.34105/j.kmel.2023.15.024>
- Jeong, A. C., Wong, R., & Mbanzabugabo, J. B. (2025). A systematic review of concept mapping and critical thinking: methodological gaps & research directions. *Educational Technology Research and Development*, 73, 3542–3567. <https://doi.org/10.1007/s11423-025-10562-2>
- Jeong, A. C. (2025). *Knowledge mapping with jMAP*. jMAP. Retrieved from <https://sites.google.com/site/causalmaps/jmap>
- 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*, 23(12), 1257–1269. <https://doi.org/10.1080/09500690010025058>
- Kinchin, I. M. (2011). Relating knowledge structures to learning styles and university teaching. In S. Rayner, & E. Cools (Eds.), *Style Differences in Cognition, Learning,*

- and Management: Theory, Research, and Practice (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*. Doctoral dissertation, The Florida State University, Tallahassee, USA. Retrieved from <https://www.proquest.com/docview/1034741996?sourcetype=Dissertations%20&%20Theses>
- McCrudden, M. T., Schraw, G., & Lehman, S. (2009). The use of adjunct displays to facilitate comprehension of causal relationships in expository text. *Instructional Science*, 37, 65–86. <https://doi.org/10.1007/s11251-007-9036-3>
- Novak, J., & Cañas, A. J. (2007). Theoretical origins of concept maps, how to construct them, and uses in education. *Reflecting Education*, 3(1), 29–42. Retrieved from <https://www.reflectingeducation.net/index.php/reflecting/article/view/41/2007>
- Ruiz-Primo, M. A., & Shavelson, R. J. (1996). Problems and issues in the use of concept maps in science assessment. *Journal of Research in Science Teaching*, 33(6), 569–600. [https://doi.org/10.1002/\(SICI\)1098-2736\(199608\)33:6%3C569::AID-TEA1%3E3.0.CO;2-M](https://doi.org/10.1002/(SICI)1098-2736(199608)33:6%3C569::AID-TEA1%3E3.0.CO;2-M)
- Schroeder, N. L., Nesbit, J. C., Anguiano, C. J., & Adesope, O. O. (2018). Studying and constructing concept maps: A meta-analysis. *Educational Psychology Review*, 30, 431–455. <https://doi.org/10.1007/s10648-017-9403-9>
- Sharma, T., Tiwari, N., & Kelkar, D. (2012). Study of difference between forward and backward reasoning. *International Journal of Emerging Technology and Advanced Engineering*, 2(10), 271–273. Retrieved from <https://ifa.or.id/wp-content/uploads/-test-study-of-difference-between-forward-and-backward-reasoning.pdf>
- Shin, H. S., & Jeong, A. (2021). Modeling the relationship between students' prior knowledge, causal reasoning processes, and quality of causal maps. *Computers & Education*, 163, 104113. <https://doi.org/10.1016/j.compedu.2020.104113>
- Sweller, J., Clark, R. E., & Kirschner, P. A. (2011). Teaching general problem solving does not lead to mathematical skills or knowledge. *EMS Newsletter*, 79, 41–42. Retrieved from <https://ems.press/content/serial-issue-files/13696>
- Taricani, E. M., & Clariana, R. B. (2006). A technique for automatically scoring open-ended concept maps. *Educational Technology Research and Development*, 54, 65–82. <https://doi.org/10.1007/s11423-006-6497-z>
- Tversky, A., & Kahneman, D. (1980). Causal schemas in judgments under uncertainty. In M. Fishbein (Ed.), *Progress in Social Psychology* (pp. 49–72). Erlbaum.
- Tversky, A., & Kahneman, D. (1982). Causal schemas in judgments under uncertainty. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under Uncertainty: Heuristics and Biases* (pp. 117–128). Cambridge University Press. <https://doi.org/10.1017/CBO9780511809477.009>
- 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.
- 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*, 52, 87–94. <https://doi.org/10.1016/j.nedt.2017.02.018>