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Exploring Interactions Between Computational and Critical Thinking in Model-Eliciting Activities Through Epistemic Network Analysis

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Abstract. In this exploratory study, we used Epistemic Network Analysis (ENA) as an analytic tool to help us better understand the possible interactions and structural connections between computational thinking and critical thinking as elicited in an open-ended authentic problem-solving task that was solved collaboratively. We found that, although students' final solutions and solving processes were qualitatively different, the structural connections found in ENA are quite similar among all teams. We interpret this as a direct reflection of the nature of the task, which is complex and open-ended, and therefore, allows for multiple possible solutions. However, the underlying structure appears to be stable, which contributes to validating the purposeful design of the activity to elicit the construct of computational thinking. Moreover, we observed that during the collaborative solution process, all teams made strong connections between elements of critical thinking and computational thinking that evolved over time. Graphs that were generated by ENA display the diversity in student thinking, as well as a similar epistemic structure in the solution of the model-eliciting activities. The interactions between critical thinking and computational thinking are evident, although components of these constructs were elicited in different ways in each team's solution.

Keywords: Models and modeling · Model-eliciting activities · Computational thinking · Critical thinking · Epistemic network analysis · STEM education · 21st century competencies

1 Introduction

Important dimensions of human competence have been identified as valuable for many centuries to achieve local and global prosperity for the common good in areas that include: education, work, health, and other life contexts. However, what distinguishes the recently called "21st century competencies" is the goal of *deeper learning* [1], to prepare next generation of students attaining strong levels of mastery across multiple areas of skill and knowledge. The role of education is even more critical in supporting the preparation in these competencies, which include: *problem solving*, *critical*

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thinking, *communication*, *collaboration*, and *self-management*. Recently, business leaders and researchers have joined educators in their efforts and commitment for a broader and more diverse population to develop these competencies in ways that can be extended and transferred to other situations beyond school to solve new problems in multiple settings [2].

However, little is known about the epistemic nature of these 21st century competencies, how they develop, and the interactions and structural connections that exist among them. Moreover, more needs to be learned about rich problem-solving contexts in which these competencies emerge and develop to prepare the next generation so that *all* students have the opportunity to succeed beyond school in a technology-based age of information [3, 4].

2 Theoretical Framework: Models and Modeling Perspective, Computational Thinking and Critical Thinking

2.1 Models and Modeling Perspective

A *Models & Modeling Perspective* is centered on the nature of students learning mathematics when they interpret real-life situations and have the need to "mathematize" in order to predict, describe, explain, or construct mathematically significant systems [5]. This perspective proposes *model-eliciting activities* (MEAs) as authentic open-ended collaborative tasks to be solved by groups of 3–4 students. In the way MEAs are designed, the solution calls for a mathematical model to be used by an identified client, or a given person who needs to solve a real-life problem [6]. In order for the client to implement the model adequately, the students must clearly elicit their thinking process and justify their solution. Thus, they need to describe, explain, manipulate, or predict the behavior of the real-world system to support their solution as the best option for the client. As in real life, there is not a single solution, but there are optimal ways to solve the problem [6, 7].

From a *Models & Modeling Perspective*, models are conceptual systems embedded in representational media and developed for a particular purpose [5]. MEAs are designed to focus on richer, deeper and higher-order understandings of relevant constructs that provide the foundation for mathematical reasoning. In addition, MEAs make learners' thinking visible through the multiple representations students use in the solution process as they continuously interpret and re-interpret the goals and givens in authentic problems [7]. Thus, students' models involve dynamic representational fluency among written, spoken, constructed, and drawn media as they revise and refine their thinking [5].

As students engage in the modeling process, they elicit their understanding of relevant mathematical constructs, while also developing competencies that are needed for success in solving real-life problems. Relevant competencies include *critical thinking, communication, collaboration, and self-management* [4, 8, 9].

2.2 Computational Thinking

C*omputational thinking (CT)* is a construct that has gained much relevance especially in the past decade as a form of literacy and a powerful skill that is needed for success beyond school in a technology-based age of information, and which extends beyond programming [e.g. 15, 16]. More recent conversations focus on the need to provide access to computational thinking to all students in K-12 classroom settings, promoting effective learning environments for students to develop and learn these foundational conceptual tools, and extend this knowledge to other contexts in which new problems can be solved [2, 4, 16].

Computational thinking is defined as the processes in formulating problems and their solutions so that these can be effectively carried out by anyone, and not only by computer scientists [17]. Computational thinking has been considered “the highest order of problem-solving” [18] and a necessary skill that all individuals should develop in order to thrive and become active citizens in our technology-driven world [19].

Computational thinking builds on power and limits of computing processes, allowing students to solve problems, design systems and understand human behavior by thinking recursively, parallel processing and recognizing virtues and dangers of any activity [20].

In this study we use a characterization of computational thinking as a collection of cognitive problem-solving skills that include the ability to: (a) decompose: or break a problem down into smaller, more manageable parts; (b) recognize patterns: or finding similarities between items; (c) abstract: or remove details to simplify a solution so that it can be generalized; and (d) create algorithms: or automate processes by designing a sequence of logical instructions to facilitate a solution [24]. Consistent with this approach, computational thinking has also been associated with modeling, especially when the focus is on abstraction as a process and a product, as when a problem calls for the need to solutions that are reusable and generalizable to different contexts [5, 9, 21, 22].

2.3 Critical Thinking

Critical thinking (CritT) is considered an essential aspect of higher order understanding highly regarded by different stakeholders in education, research, and industry [1, 3]. Over the past years, several frameworks have been developed to identify and analyze critical thinking emerging from collaborative group problem solving [8, 27, 30]. Studies show that MEAs successfully supports the full process of critical thinking as described by Dewey [31] and Ennis [28–30]. For this study, we use a framework that has been used in previous studies to characterize critical thinking in the context of MEAs [8], using five descriptors of the process, including:

1. Initiation: Identification of a common question or problem and discussion to ensure that question or problem is understood by the group.
2. Exploration: All discussion which expands upon the problem or question to support formation of a solution.
3. Solution: Positing an answer to the question or problem and the initial explanation of that answer or solution.

4. Judgment: All discussion where the answer or solution is debated, modified, or tested.
5. Resolution: When the participants agree upon a final solution or answer.

2.4 Studying the Relationship Between Computational Thinking and Critical Thinking

There are only a few studies exploring the connections between computational thinking and critical thinking (e.g., [17, 32]). While some approaches identify similarities and differences in the operationalization of these constructs, there is agreement that they both emerge within problem-solving situations. However, as a field we're still developing our understanding on an epistemic structure for computational thinking, critical thinking, and the possible connections between these two; and more specifically, when students engage in open-ended collaborative problem-solving activities that are designed for *all* students to participate and learn.

A better understanding of the characteristics of learning environments in which computational thinking emerges, the nature of computational thinking, and how it relates to other foundational 21st Century conceptual tools such as critical thinking are of utmost importance to articulate an educational plan that fosters "computational thinking for all" [3, 18].

In this exploratory study, we propose utilizing a model-eliciting activity called the Tic-Tac-Toe Problem that was purposefully designed to elicit computational thinking [33] and identify whether critical thinking also emerges in students' solution processes. Then, we use Epistemic Network Analysis (ENA) to explore the structural relationship between computational thinking and critical thinking as these emerge while students solve the Tic-Tac-Toe Problem.

3 Research Questions and Rationale

We report an exploratory study guided by two research questions:

- What is the structural relationship between computational thinking and critical thinking as both constructs emerge in the context of a genre of open-ended authentic collaborative group tasks called model-eliciting activities (MEAs)?
- How do computational thinking and critical thinking dynamically interact and evolve during the collaborative process, and how is this interaction characterized as students solve the model-eliciting activity?

Although some authors have identified connections between computational thinking and critical thinking (e.g., [17]), there is a lack of theoretical frameworks that explicitly describe how both constructs are connected [32]. In this study, we use ENA [14] to identify and quantify connections between critical thinking and computational thinking emerging while students solve a genre of open-ended collaborative group tasks called MEAs [5]. Explicitly articulating these connections will increase our understanding of the epistemic connections between critical thinking and computational thinking as students engage in model-eliciting activities that are purposefully designed for *all students* to participate and elicit their understanding of these relevant constructs. Therefore, this study is an important step to provide broader access for *all* students to develop these highly sought skills.

4 Modes of Inquiry

Quantitative Ethnography is a methodological approach that uses qualitative and quantitative approaches to understand data-rich evidence about the discourse of cultures [34]. It respects the insights gained by ethnography and applies the power of statistical techniques. An ethnographer makes observations and collects rich data to understand patterns of discourse of the culture being studied. Quantitative Ethnography uses inferential statistical techniques to facilitate systematic interpretations to find meaning in shared and learned patterns of values and systems of symbols (e.g., language) [34–36].

Discourse analysis is the study of language at use in the world, where language is viewed as socially constructed and related to situated contexts. It deals with the interpretive processes that individuals use to give meaning in social, cultural, and political terms [10, 11, 34]. ENA is a theory-driven technique that allows for a more comprehensive discourse analysis of large datasets related to how learning occurs by takings advantage of combining powerful qualitative and quantitative analytical tools [12].

According to Shaffer & Ruis [12], an epistemic frame involves "the actions and interactions of an individual engaged in authentic tasks" (p. 176). ENA is a method for the analysis of cognitive networks by modeling the association between elements of complex thinking. The connections among cognitive elements are more important than studying those elements in isolation. ENA is used to examine the connections and uses visualization and statistical techniques to identify patterns. It quantifies the co-occurrence of concepts within a conversation [12, 13, 34, 36].

ENA analyzes data segmented, based on the principles of discourse analysis, starting with lines and grouping the conversations in stanzas. Relationships are calculated and depicted graphically and to look at the co-occurrence of concepts in the conversations that students have while learning a concept.

Several studies based on *Models & Modeling Perspectives* have relied on discourse analysis to study underlying meaning from students' solutions in MEAs [10, 11]. These studies have helped us better understand the nature of the modeling process and the constructs students develop in their solution models, as their thinking is elicited through multiple representations [5]. In this study, we propose that a *Models & Modeling* perspective is consistent with the approach to learning proposed by *epistemic frame theory* [12]. Moreover, we argue that students' modeling processes can be analyzed as an epistemic frame, considered as "the actions and interactions of an individual engaged in authentic tasks" such as MEAs. Therefore, we explore ENA as a novel theory-based approach to better understand the nature of the constructs that students elicit, develop, and co-develop within a problem-solving episode of a MEA. In this way, ENA can help shed some light in better understanding the possible interactions and structural connections among relevant competencies previously mentioned, such as computational thinking and critical thinking.

5 Methods

We designed the Tic-Tac-Toe model-eliciting activity for high school students to elicit computational thinking. In the context of the Turing Test and artificial intelligence [37], we asked students to work in teams and create an algorithm for a computer game that would allow the machine to never lose in the game of tic-tac-toe when playing with a human [33]. Clear objectives in the MEA allow the students to continuously judge the quality of their solution by fostering multiple opportunities for reflection and explanation [6, 7]. These aspects facilitate application and communication of critical thinking skills and other foundational conceptual tools as learners "select, filter, organize, and transform information" [8].

Our participants were a group of 11 students at a Career and Technical Education high school program in South Texas. Most students were male Hispanics and African Americans. Students were divided into three teams (3-3-4 students, respectively) and were given one hour to collaborative solve the Tic-Tac-Toe MEA. Each of the three teams produced a different solution or algorithm. The three solution algorithms were qualitatively different, and they all elicited students' ideas related to computational thinking and critical thinking. In this MEA, the algorithm produced is what we identify as a model or solution (i.e., a conceptual system that is expressed using representational systems to construct, describe, and explain behaviors of other systems).

The primary sources of data were the videorecordings of the conversations from each team while collaboratively solving the MEA. These contain multiple sets of data sources. During the recorded episodes, students were engaged in generating the solution for the MEA. The focus was on the participant interactions as they elicited and co-constructed a solution that involved computational thinking and critical thinking. The video recordings for the three teams were transcribed and time stamped.

Analytic coding methods were used for each of the three transcripts [37]. Based on the theoretical characterization we used for each construct, two coding schemes were used: one for critical thinking (CritT), consisting of five categories: initiation, exploration, solution, judgment, and resolution; and one for computational thinking (CT), consisting of four categories: decomposition, abstract, patterns, and algorithms. Table 1 provides the code book we used including the name of the code (construct/category), definition of the code, and examples of the code or excerpts of the transcripts illustrating each category.

Table 1. Code book containing code names, definitions, and examples.

Name	Definition	Examples
Initiation (CritT)	Identification of a common question or problem	*"We have to win every time? I kind of want to do that"*
Exploration (CritT)	All discussion which expands upon the problem or question to support formation of a solution	*"are you talking about the corners?"*
Solution (CritT)	Positing an answer to the question or problem	*"Yeah, yeah. Like you put, like what I'd do is the one in the middle… I always start in the middle, and then, wherever they make a move, that's what corner… this side"*
Judgment (CritT)	All discussion where the answer or solution is debated, modified, or tested	*"… you are looking at a tie… cause if he just put it like this… no one is going to win… so… it just ah… see… no one wins."*
Resolution (CritT)	When participants agree upon a final solution	*"You start off (inaudible)… start off here… so I think… any time, yeah… (inaudible) doesn't matter cause you'd win anyways… so I guess…(inaudible) strategy we start in the corners… to be the winner…"*
Decomposition (CT)	Break a problem down into smaller parts	*"see… I just went (inaudible). You can start in the corner… it's not… perfect but it wins, sometimes, like if someone knows what you're doing, they'll take the corners too… here… there you go…"*
Patterns (CT)	Finding similarities between items	*"I'd start at the corner here, these corners"*
Abstract (CT)	Remove details for generalization	*"Well, these are all the rules… all these rules are (inaudible) to follow us. So this is… there's a circle starting in every single spot… like that's the first rule, telling the human where to go first."*
Algorithm (CT)	Automate processes by designing a sequence of logical instructions	*"Right here. So I guess that is the way to beat it, if they start in any kind of corner, I guess, you could just put it on the opposite side, that just ruins your rhythm."*

Two separate raters coded each transcribed line of the discourse by participant, identifying each corresponding characteristic for computational thinking and critical thinking and coded using a 1 if a specific characteristic in our code book was evident and a 0 otherwise. When raters identified different codes for the same line, social moderation was used to find an agreed-upon code.

A database was produced and configured for ENA. Lines in the transcript were organized into stanzas, and binary coding was produced for each line of dialogue. We defined the units of analysis as all lines of data associated with a single value of team subsetted by participant (i.e., student).

Once coding was finalized and verified, ENA [12, 14, 34] was applied to this data using the ENA Web Tool (version 1.7.0) [31, 39]. The ENA algorithm uses a moving window to construct a network model for each line in the data, showing how codes in the current line are connected to codes that occur within the recent temporal context [40], defined as 20 lines (each line plus the 19 previous lines) within a given conversation. The resulting networks are aggregated for all lines for each unit of analysis in the model. In this model, we aggregated networks using a weighted summation in which the networks for a given line reflect square root of the product of each pair of codes.

Our ENA model included the identified codes for critical thinking and computational thinking: Initiation, Exploration, Solution, Judgment, Resolution, Decomposition, Pattern, Abstract and Algorithm. We defined conversations as all lines of data associated with a single value of Activity. For example, one conversation consisted of all the lines associated with the Tic-Tac-Toe activity.

The ENA model normalized the networks for all units of analysis before they were subjected to a dimensional reduction, which accounts for the fact that different units of analysis may have different amounts of coded lines in the data. For the dimensional reduction, ENA performed a singular value decomposition (SVD), projecting and centering the data without rescaling it. This projection maximized the variance accounted for the data in a two-dimensional orthogonal space: SVD1 and SVD2, that we then interpreted in relation to the research questions and our analytical framework.

ENA generated mean network graphs that show the two-dimensional orthogonal space generated by SVD1 and SVD2. We analyzed the graphs based on the strength of the connections between nodes representing our operational definition for computational thinking (abstract, decompose, recognize patterns and create algorithms) and critical thinking (initiation, exploration, solution, judgment, and resolution) for each of the teams: 1, 2, and 3. We verified these interpretations by going back to the transcripts and validating with the discourse.

6 Results and Interpretations

Figures 1, 2 and 3 provide visual representations of the ENA which show connections among cognitive elements of computational thinking and critical thinking, respectively for each participating Team 1, Team 2, or Team 3. In the mean network graph showing the representation of the shared space for the three teams simultaneously, we see that the amount of variance explained by the variables represented in axes SVD 1 and SVD 2 is almost 55% of the total variance: 32.5% for SVD 1 and 22.4% for SVD 2. In this section, we provide our interpretations of the ENA Models. First, we report our interpretations of the space generated by SVD 1 and SVD 2. Then, we interpret the ENA Models generated for Teams 1, 2, and 3 in terms of the co-occurrences of the different characteristics of Critical Thinking and Computational Thinking.

We propose an interpretation of the structural connections between computational thinking and critical thinking elicited during the Tic-Tac-Toe problem-solving episode by focusing on the structure of the connections in the data as displayed in each graph. Then, we extended our interpretation to analyze the orthogonal space of SVD 1 and SVD 2, based on the position of each pair of coordinates or nodes corresponding to each characteristic of computational thinking and critical thinking in this two-dimensional space.

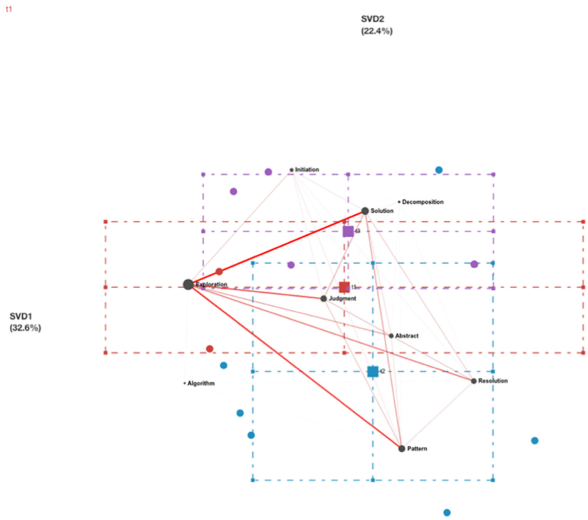

Fig. 1. Network graph for Team 1, showing centroids and confidence intervals.

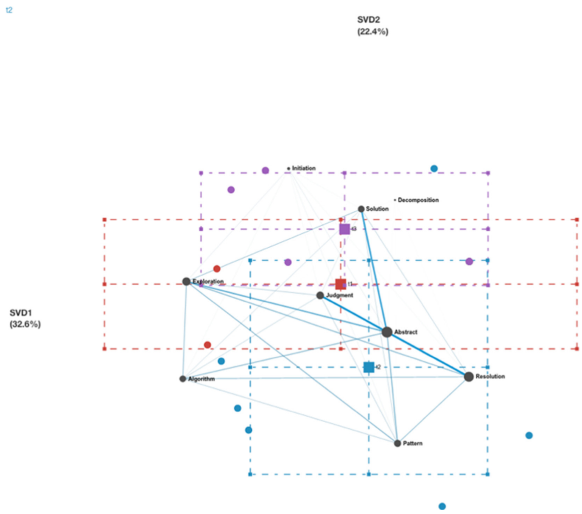

Fig. 2. Network graph for Team 2, showing centroids and confidence intervals.

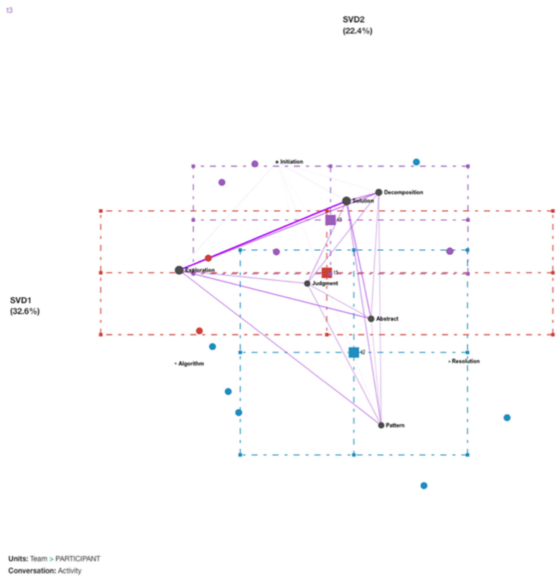

Fig. 3. Network graph for Team 3, showing centroids and confidence intervals.

6.1 Comparing Graphs for Teams 1, 2 and 3

ENA was performed on the co-occurrences of each pair of components and the network formed provides a model of the structure of these connections. Based on this ENA, we interpret the network models as the structure of connections among the elements of computational thinking and critical thinking elicited by the students' discourse as they solved the Tic-Tac-Toe MEA. Thicker lines within the network represent stronger connections, whereas thinker lines are weaker connections.

For example, the network for Team 1 (Fig. 1) builds the strongest connections between Exploration (CritT) and Solution, and between Exploration (CritT) and Patterns (CT). The connections between Exploration (CritT) and Judgment (CritT), and between Exploration (CritT) and Resolution (CritT) are also relevant. This indicates that as Team 1 recursively used exploration as a powerful strategy that allowed them to concurrently test their solution, find patterns, and judge whether their proposed solution did indeed allow the computer to win the game of Tic-Tac-Toe regardless of where the human might place their mark. Based on the discourse used by this team, Exploration was an important mediator for them to advance through cycles of critical thinking as the Team articulated a solution. Exploration (CritT) seems to have driven all other components of CritT and CT, as it had the highest frequency and connected to all other codes. As Team 1 systematically explored different cases in the tic-tac-toe game, they found patterns and solutions using their judgment.

In terms of the epistemic connections between critical thinking and computational thinking for Team 1, ENA indicates that the strongest connection was between Exploration (CritT) and Patterns (CT). This is consistent with the description in the qualitative descriptive analysis revealing that the team used a systematic trial-and-error approach to solving this activity. Team 1 systematically played dozens of tic-tac-toe games, assessing multiple possibilities in an organized way that allowed them to find patterns. For example, they began questioning whether the computer first needed to place a mark in one of the corners, at the center edge, or in the middle. After exploring multiple possible games, they found patterns that allowed the team to judge that a good strategy for the computer to win is to always mark one of the corners. Exploration and finding patters slowly generated solution strategies for the computer, and it was not until the very end that they were able to abstract this knowledge to come up with an algorithm for the computer to not lose the game. In subsequent analyses, we anticipate developing an ENA trajectory to better understand the epistemic dynamic cycles over time for each team as they solved the activity.

The network for Team 2 displayed in Fig. 2 shows the strongest connections between Resolution (CritT) and Judgment (CritT). However, the graph shows that this strong connection is mediated by Abstract (CT). Moreover, Abstract (CT) also has strong connections with all other components of critical thinking, including Solution (CritT), Resolution (CritT) and Exploration. Co-ocurrences among components of computational thinking are not as strong, but still evident, between Abstract (CT) and Pattern (CT). This team created several rules, or algorithms, and then tested these rules with concrete possible scenarios in the tic-tac-toe game. In contrast with Team 1 who had an approach from particular case-by-case to generalizing, Team 2 created more general rules and then tested to see if they would hold under particular cases they identified. Thus, Team 2 went from more general to particular cases, and this is illustrated in their network model showing more connections between Abstraction (CT) with other characteristics of critical thinking and with Patterns (CT). Moreover, the graph also shows some weaker connections with Algorithms (CT) and other characteristics.

The network model for Team 3 displayed in Fig. 3 indicates that the strongest connection was between Exploration (CritT) and Solution (CritT). However, Exploration (CritT) was also connected with Abstract (CT), Decomposition (CT) and Patterns (CT), which are all elements of computational thinking. Another interesting set of connections Team 3 made, although weaker, was between Abstract (CT) and Solution (CritT), between Abstract (CT) and Judgment (CritT), and between Abstract (CT) and Decomposition (CT). From the network model, it appears that judgment and abstraction mediate the many co-occurrences this team made among components of critical thinking and computational thinking.

The strategies used by Team 3 appear similar to the ones from Team 1 in that they also went from playing many instances of the tic-tac-toe game, and using particular cases to generalize to a solution. Early in their team activity, one of the members proposed a winning strategy from the beginning (i.e., having the computer go first and take a corner). However, other team members did not appear to understand that this was a more abstract solution and they continued playing instances of the tic-tac-toe game until they found enough patterns to arrive to the same conclusion as their peer had suggested earlier. In this process, the students try different strategies and come up with partial solutions which they verify and integrate to a more generalized solution at the end of the episode.

Looking at the centroids for Teams 1, 2, and 3 in these graphs, as well as the respective confidence intervals, we observe that the confidence intervals all overlap. Considering each centroid as a summary of the ENA network for the three teams, we see that all the centroids are relatively close to each other and aligned. Both, the closeness of the centroids and the overlap of the confidence intervals indicate that the epistemic frames between teams is similar in the variables described by SVD 1 and SVD 2. Although this is visually evident, we also conducted a Mann-Whitney U Test for a pairwise mean comparison for all teams (Team 1 vs Team 2, Team 1 vs. Team 3, and Team 2 vs. Team 3). We found no significant difference between teams.

Although it is clear from the ENA for each Team, and their respective network models, that the three teams used different strategies in their solutions, we interpret this statistical result as content validity of the task, that the MEA did indeed elicit students' computational thinking and critical thinking for all teams; and that, although qualitatively different, there is a strong interaction between these two constructs as students generate their solutions to the task. We also noticed that, although each team did show evidence of eliciting computational thinking and critical thinking during the Tic-Tac-Toe problem-solving episode, each of the three teams generated distinct concept spaces which characterize their cognitive processes related to these two constructs.

6.2 Interpretation of SVD 1 and SVD 2

Observing the positions of the network graph nodes—and the connections they define, we interpreted the dimensions of the projected space and describe the positions of plotted points in the space. Therefore, in making interpretations of the underlying constructs for SVD 1 and SVD 2, we notice the following:

- SVD 1 shows two sets of characteristics for computational thinking and critical thinking that are grouped and organized based on what appears to be describing a continuum for *problem solving,* defined as a continuum from givens to goals [5]. For example, we observe that on one end (positive side of the axis, from greatest to least magnitude) are: resolution (CritT); decomposition (CT), pattern (CT), and abstract (CT) almost at the same level, solution (CritT), and judgment (CritT). These are all characteristics that correspond to processes that students engage in with data or other cognitive tools and resources that are generated by their own team during the problem-solving episode as they develop their solution. On the opposite end (negative side of the axis) are: initiation (CritT), algorithm (CT), and exploration (CritT). Descriptors on this second group seem to be characteristics that correspond to processes that students follow based on information provided directly in the problem statement.
- SVD 2 shows two sets of characteristics for computational thinking and critical thinking that are grouped and organized based on what appears to be a continuum for *deeper learning*. [1] On the one end (negative side of the axis, from greater to least magnitude) are: pattern (CT), algorithm (CT) at the same level as resolution (CritT), and abstract (CT). These all seem to be characteristics that are more abstract and transferable to different problem-solving situations beyond the context in which the Tic-Tac-Toe MEA is embedded. On the opposite end (positive side of the axis) are: judgment (CritT) almost at the same level as exploration (CritT), solution (CritT), decomposition (CT), and initiation (CritT). Descriptors on this second group seem to be characteristics that are more problem-specific and situated within the Tic-Tac-Toe MEA and which have a more interpretive aspect from the team members.

7 Conclusions and Next Steps

In this exploratory study, we used ENA as an analytic tool to help us better understand the possible structural connections between computational thinking and critical thinking as elicited in a collaborative authentic problem-solving task called the Tic-Tac-Toe model-eliciting activity (MEA). We found that while solving this MEA, the structural connections elicited by the three teams of students were very similar. We interpret this as a direct reflection of the nature of the task, which is complex and open-ended, and therefore, allows for multiple possible solutions. We found that all teams made strong connections between critical thinking and computational thinking, although the solution processes were qualitatively different. Nevertheless, we found that Exploration (CritT) and Abstraction (CT) appear to be key mediating components that facilitate connections with other characteristics of critical thinking and computational thinking as students elicit their solution models.

Graphs that were generated by ENA display the diversity in student thinking, as well as a similar epistemic structure in the solution of the MEA. The interactions between critical thinking and computational thinking are evident, although components of these constructs were elicited in different ways in each team's solution.

This study warrants further exploration on the design of model-eliciting activities as an efficient learning environment that elicits computational thinking and critical thinking, and be able to better understand the nature of these two constructs, as well as the structural connections that are generated. Moreover, this study opens future studies to use ENA to better understand the dynamic epistemic nature of modeling cycles that students engage in with MEAs, in which they express, test, revise, and refine a progression of preliminary solutions of possible tic-tac-toe game strategies.

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