EPISTEMIC NETWORK ANALYSIS TO STUDY GENDER EQUITY IN CYBER SECURITY: WOMEN'S CONTRIBUTIONS TO COMPUTATIONAL THINKING IN MODEL-ELICITING

by

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DEDICATION

To my husband, Gonzalo, you are my rock.
My precious kids, Emi, Clems y Cris, you are my light.
My parents, Tita y Juan Manuel, you are my example.
And to my brothers, Mau y Juan, you are my joy.

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EPISTEMIC NETWORK ANALYSIS TO STUDY GENDER EQUITY IN CYBER SECURITY: WOMEN'S CONTRIBUTIONS TO COMPUTATIONAL THINKING IN MODEL-ELICITING ACTIVITIES

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ABSTRACT

This study examines high school women's and men's cognitive engagement in computational thinking elicited through Model-Eliciting Activities (MEAs). The purpose is to understand potential gender differences that could inform strategies for increasing women's representation in STEM fields. Discourse analysis was used to examine conversations between an all-women team and an all-men team collaboratively solving a Tic-tac-toe MEA. Utterances were coded for computational thinking skills (decomposition, pattern recognition, abstraction, and algorithms) and indicators of cognitive engagement (self-regulation, justification, questioning, giving directions, and uptake). Epistemic network analysis (ENA) modeled relationships between codes based on their co-occurrence. ENA visualizations revealed the interconnections between computational thinking and engagement for each team. Subtracted ENA networks highlighted differences between the teams. The women frequently used questioning and justification around breaking problems into smaller parts (decomposition). The men relied more on justifying answers and directing each other in abstracting patterns and algorithms. Both teams succeeded in developing computational thinking models, but in different ways reflecting their unique collaborative engagement styles. Results suggest tailored strategies aligned with women's and men's distinctive learning processes are needed to optimize their

computational thinking development. Model-eliciting activities show promise for facilitating cognitively engaging, collaborative STEM learning for diverse students. Ultimately, examining gender dynamics provides insights into creating supportive, empowering STEM learning environments where all students can thrive. This study offers a model for understanding and promoting gender equity in STEM education.

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CHAPTER ONE: INTRODUCTION

Background

This study responds to the notable absence of women in computer-related fields. The workforce shortage in this area is predicted to 1.5 million unfilled roles in the cybersecurity sector alone (Bagchi-Sen et al., 2010). With the intensifying competition, preparation in computer-related majors is vital to economic health and national security interests. There is an increase of demand for skilled professionals in the science, technology, engineering, and mathematics (STEM) fields in general and in computer-related fields in particular (Knight et al., 2016).

Underrepresentation of women in these fields is of national concern. Including women in the workforce could help solve part of the shortage problem given that women represent 50% of the American population (Cohoon & Aspray, 2006; Dasgupta & Stout, 2014). Previous research shows us that bringing diversity and women into the workforce will help diminish and ultimately eliminate the gap between professionals needed and students graduating from these areas. Casey, et al. (2020) suggest women appear to be more motivated by different content and collaboration practices than men when it comes to cybersecurity. The context and the collaboration are areas more women focus on.

Despite all the efforts done in outreach and education, women still have lower representation in STEM fields, and less than 20% of female students in high school are declaring a STEM major (Blackburn, 2017). Women's participation in science, technology, engineering, and mathematics (STEM) fields has been a subject of intense research and policy focus in recent years. Recent research studies have concluded that there is no evidence consistent with men's advantage; women and men perform similarly when it comes to testing and assessing the ability to perform in STEM-related subjects or tasks (Riegle-Crumb, 2016). High school students believe in gender equality in math; students no longer endorse traditional stereotypes. The limited utility of theories focusing on the difference in skills and abilities suggests that theories of gender as a social structure may be more useful to understand the inequalities now present (Riegle-Crumb et al., 2012). Eccles' Situated Expectancy-Value Theory suggests that stereotypes play a crucial role in shaping individuals' beliefs about their abilities and interests, which in turn influence their behavior and choices within specific domains.

Despite progress in some areas, women remain underrepresented in many STEM fields, particularly at higher levels of education and employment. Research studies have shown that the lack of women in STEM fields can have negative consequences for society as a whole, including a loss of talent and innovation (National Academies of Sciences, 2018). In addition, women in STEM fields often face challenges related to gender bias, discrimination, and work-life balance, which can limit their opportunities for advancement and contribute to a gender pay gap (National Academies of Sciences, Engineering, Medicine, 2018; National Science Foundation, 2019) .

Statistics illustrate the extent of the underrepresentation of women in STEM fields. For example, in the United States, women earn only 18% of bachelor's degrees in computer science, 19% of bachelor's degrees in engineering, and 20% of bachelor's degrees in physics ((National Science Foundation, 2019). Similarly, women hold only 28% of STEM jobs in the United States, despite comprising nearly half of the overall workforce (National Science Foundation, 2019).

Efforts to address the underrepresentation of women in STEM fields have focused on a variety of strategies, including increasing access to educational opportunities, providing mentorship and support networks, and promoting gender equity policies in the workplace (National Academies of Sciences, Engineering, and Medicine, 2018). The underrepresentation of women in STEM fields has significant consequences for both individuals and society. While progress has been made in some areas, continued research and policy efforts are needed to address the underlying causes of this issue and promote greater gender equity in STEM fields. To effectively think of include women in STEM we need to go back to the definition of equity. Equity can be defined as: "the access to resources and opportunities that recognize, respect, and value differences among people and contexts while also disrupting, rather than reproducing, injustice and promoting justice-oriented futures" (Calabrese Barton & Tan, 2019, p. 618).

Men and women often have different beliefs about their abilities, the value of STEM fields, and their expectations for success in these areas, which can explain gender differences in participation in STEM fields. For example, research studies have found that women often have lower self-efficacy beliefs in STEM fields when compared to men (Eccles & Wigfield, 2020a) . This can lead to a lack of confidence and a decreased likelihood of women pursuing careers in STEM. Moreover, women are often less likely to perceive the task value of STEM fields, which can also contribute to gender disparities in participation (Eccles & Wigfield, 2020a; Gladstone et al., 2022)

Problem Statement

There is an impending need that has been established to improve equitable access to high-quality learning experiences in the STEM field (AIR, 2016). Students and educators need to design curricula and instruction in STEM so that all students are cognitively engaged and participate in the learning environments. Barriers in equitable opportunities in STEM education limit the access of students, especially from historically underrepresented minorities, including women, to have science-empowered futures. Students want and should be given opportunities to participate and learn STEM by doing something that "actually matters" to them (Calabrese Barton & Tan, 2019).

In an era where computational thinking emerges as a fundamental skill for all individuals, there is an increasing concern regarding equity in cognitive engagement, particularly for women. It is imperative to design classroom activities that ensure all students, regardless of gender, have equitable opportunities and encouragement to develop and harness computational thinking capabilities.

Purpose Statement

This study proposes to examine women's and men's engagement in a Model Eliciting Activity (MEA) that elicits computational thinking, analyzing the relationship between cognitive engagement and computational thinking (CT) for women and men. Focusing on how women engage, as described by the Situated Expectancy Value Theory, this study seeks to explore potential differences between men and women in eliciting computational thinking. The primary objective of this study is to enhance our understanding of women's cognitive engagement in STEM activities, with a specific focus on MEAs that elicit computational thinking, and to investigate whether there are gender differences in the ways in which men and women elicit and cognitively engage in computational thinking.

Moreover, the study's seeks to enhance our understanding of women's cognitive engagement in a STEM-related activity called model-eliciting activity, designed to elicit computational thinking. It also aims to identify any potential differences in the strategies employed by men and women to elicit and cognitively engage in computational thinking.

Research Questions

- **RQ1.** How does student cognitive engagement relate to computational thinking while solving the Tic-tac-toe MEA?
- **RQ2.** What are the similarities and distinctions between the two teams, depending on team members' gender (one all-women team and one all-men team)?

Conceptual Framework

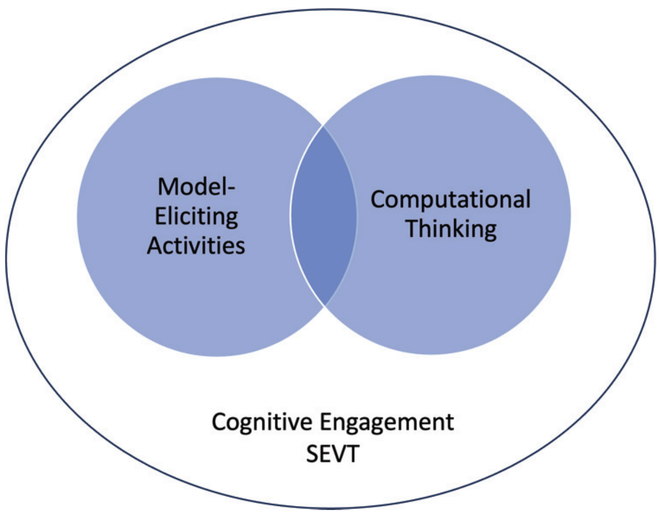

Figure 1

Conceptual Framework

Figure 1 illustrates the convergence of the theoretical frameworks, forming the foundation for our conceptual frameworks. Students, segregated into single-gender groups (all-women and all-men), will engage with a meticulously designed Model Eliciting Activity (MEA) that adheres to its six design principles. Through this, they will elicit computational thinking in model creation. To understand the cognitive engagement of the women and to contrast it with the men’s team, the study relies on the cognitive engagement as part of the Situated Expectancy Value Theory.

In the context of a Models & Modeling Perspective, models are conceptualized as systems embedded within various forms of representational media, crafted with a specific purpose in mind (Lesh & Doerr, 2003). Model Eliciting Activities (MEAs) are designed to facilitate a profound, comprehensive understanding of key constructs that serve as the basis for mathematical reasoning. Furthermore, MEAs enable the visualization of learners' cognitive processes through the diverse representations students utilize in the problem-solving process, as they continuously decipher and reinterpret the tasks and given information in real-world problems (Carmona & Greenstein, 2009). As such, students' models exhibit dynamic representational proficiency spanning written, spoken, constructed, and illustrated media, as they persistently fine-tune and evolve their thinking (Lesh & Doerr, 2003).

Computational thinking (CT) has gained relevance as a crucial construct over the past decade. It is increasingly viewed as a vital literacy and a potent skill necessary for success in the information age saturated with technology, and its relevance goes beyond programming (Shute et al., 2017; Wing, 2008). Current discussions emphasize the importance of making computational thinking accessible to all students in K-12 educational environments. Such access encourages conducive learning atmospheres for students to acquire and hone these foundational conceptual tools. Furthermore, it allows students to apply this knowledge in different contexts for problem-solving (Amri et al., 2019; Arastoopour Irgens et al., 2020; Brennan & Resnick, 2012).

Cognitive engagement is the degree to which a student is actively and cognitively involved in learning (Eccles & Wigfield, 2020a; Gladstone et al., 2022). This concept is grounded in the Situated Expectancy Value Theory (SEVT), which suggests that students' cognitive engagement is influenced by their beliefs, values, and goals related to learning (Eccles, 1994; Eccles & Wigfield, 2002, 2020a). SEVT proposes that students' perceptions of their ability to succeed (expectancy) and their values and interests in the learning task (value) interact to determine their level of engagement. In this way, cognitive engagement can be understood as a dynamic and situated construct influenced by individual and contextual factors.

This study focuses on understanding the cognitive engagement of students while they elicit computational thinking when solving the Tic-tac-toe Model Eliciting Activity, focusing on potential gender differences between an all-women's and an all-men's team.

Analytical Approach

Discourse analysis is used to examine the conversations among students in two separate teams based on their gender composition (one all-women and one all-men). Through this approach, I explored how each team cognitively engaged in the Model Eliciting Activity and elicited computational thinking. Conversations between teammates in both teams were videorecorded, transcribed verbatim and coded for the four categories for computational thinking, the six categories for cognitive engagement.

Epistemic Network Analysis (ENA) is used to examine the connections and uses visualization and statistical techniques to identify patterns and quantify the co-occurrence of concepts within a conversation (Bowman et al., 2021; Shaffer, 2017) With ENA, I can understand meaningful connections among the participants and focus on the quality of the connections rather than on the number of instances (Bressler et al., 2019; Shaffer, 2017; Shaffer et al., 2009). By using ENA, I was able to uncover the relationship between student cognitive engagement and computational thinking for each team. Moreover, using subtracted network analysis, I was able to compare and identify differences in the relationship between student cognitive engagement and computational thinking for the two teams.

Significance of the Study

This exploratory research study aims to understand how women cognitively engage in a Model Eliciting Activity to elicit computational thinking. Creating an equitable learning environment we can help eliminate gender biases from a younger age, ensuring both women and men have the opportunity to explore and excel in STEM (Master et al., 2016). When women and men have equal opportunities to engage in STEM, society benefits from the potential contributions of all its members, irrespective of gender (Wang & Degol, 2013). Literature tells us diverse teams approach problems from different angles and provide unique solutions, organizations with diverse workforce tend to be more profitable and innovative (Lewis, 2015).

The use of Model Eliciting activities encourages multiple perspectives. This validates a wide range of problem-solving approaches, allowing students from different backgrounds, learning styles, and thought processes to showcase their unique skills and understanding (Lesh & Doerr, 2003). Students collaboratively build models promoting equity. MEAs prioritize conceptual understanding, leveling the field for students who may struggle with traditional tasks but thrive when tasked with applying concepts (Zawojewski & Carmona, 2001) They allow students to connect personally with the content, making it more meaningful (Hamilton, 2008).

Computational thinking provides the foundation skills necessary for careers in cybersecurity, these skills include problem-solving, logic and algorithmic thinking (Wing, 2006). Equipping students with computational thinking skills prepares them for in-demand jobs that are in growing need as the world becomes increasingly digital (Crumpler & Lewis, 2019).

By promoting activities that encourage cognitive engagement in women, we are combatting stereotypes that can limit women's beliefs about their capabilities. Cognitively engaging activities can help them recognize their potential and foster their confidence and interest in STEM fields (Steele, 1997). Cognitive engagement will encourage women to follow their paths in STEM-related fields and they will become role models for future generations, creating a positive feedback loop (Stout et al., 2011).

The problem of underrepresentation of women in STEM needs to be solved early on, by providing opportunities for women to succeed and cognitively engage in classes, by motivating students and by teaching skills, such as computational thinking that will help them become successful in the future. One way to do it is by using Model Eliciting Activities.

The methodological design of this study offers profound insights into understanding group dynamics, cognitive engagement, and computational thinking within educational settings. By employing discourse analysis, the research delves deeply into the qualitative nuances of student interactions, uncovering how they construct knowledge and interpret task requirements (Gee, 2014). This analysis is further enriched by the structured application of coding to recognize conversation patterns and co-occurrences, offering a systematic framework to categorize and analyze the qualitative data (Shaffer et al., 2016). Additionally, the Epistemic Network Analysis (ENA) allows for the visualization and quantification of intricate relationships in discourse, providing a lens into how each student contributes to the collective conversation and revealing instances where they might engage and elicit computational thinking concurrently (Shaffer & Ruis, 2017). The comparative analysis between the all-women's and all-men's groups not only highlights potential gendered dynamics but also helps educators glean valuable insights for more inclusive pedagogical strategies.

Delimitations

Delimitations refer to the choices made by the researcher which define the boundaries of a study. They are used to narrow the scope of a study. The following are the delimitations for this study:

- Temporal Delimitation: The study was conducted in 2021, during the post-COVID era. This specific timing means the results might be influenced by unique academic and social challenges or advantages stemming from the pandemic's aftermath.
- Geographical Delimitation: The study was localized to a cybersecurity classroom in South Texas. This means that the findings might have a regional bias and might not be applicable to classrooms in other geographical regions or cultural settings.
- Sample Size & Composition Delimitation: The study focuses on two specific teams: one all-women team of three members and one all-men team of four members. The uneven number of members and gender separation may influence the group dynamics and conversation structures.
- Activity-Based Delimitation: The study revolves around the completion of a Model Eliciting Activity (MEA). This means that the findings are tied to this specific type of activity and might not necessarily translate to other types of classroom tasks or discussions.
- Criteria for Analysis Delimitation: The analysis was focused on instances where conversations indicated students were discussing one of the codes from computational thinking and cognitive engagement. This choice might mean other valuable or relevant conversations were not taken into consideration for the analysis. The study aimed to

identify how these codes relate and intersect between constructs. As such, other potential themes or patterns in conversation might have been overlooked.

- Methodological Delimitation: By focusing only on conversations, the study might miss non-verbal cues or other forms of engagement that could provide additional insights into group dynamics, cognitive engagement, and computational thinking processes.

In conclusion, while the delimitations serve to narrow and define the scope of the study to make it manageable and specific, they also highlight the aspects that aren't addressed or included. These are vital in providing clarity about what the study does and doesn't encompass, thus offering context for interpreting the results.

Definition of Terms

- Abstraction - A computational thinking skill involving identifying the general principles and discarding insignificant details of a problem to focus on the concepts that are relevant (Wing, 2006).
- Algorithm Design - Developing step-by-step instructions or processes for solving problems or achieving desired outcomes (Grover & Pea, 2013).
- Computational Thinking (CT) - Problem-solving processes that involve formulating problems and solutions in ways that allow the use of a computer and other tools to effectively carry out the solutions (Wing, 2006).
- Cognitive Engagement - The degree to which students are actively thinking about, focused on, and invested in the learning task, as characterized by effort, motivation, and self-regulation (Appleton et al., 2006).
- Decomposition - Breaking down a complex problem into smaller, more manageable parts that are easier to solve (Csizmadia et al., 2015).

- Discourse Analysis - The analysis of patterns of language across texts and conversations to understand how social realities and relationships are created through communicative practices (Gee, 2014).
- Epistemic Network Analysis (ENA) - A quantitative ethnographic technique that models the connections between coded elements in verbal data to identify meaningful patterns and relationships (Shaffer et al., 2009).
- Model Eliciting Activities (MEAs) - Open-ended problems that require students to develop mathematical or scientific models that satisfy a set of criteria and can be generalized to solve broader classes of problems (Lesh et al., 2003).
- Pattern Recognition - Identifying similarities or common relationships between the elements of a problem situation (Lye & Koh, 2014).
- Situated Expectancy Value Theory (SEVT) - A motivation theory positing that students' expectancy beliefs about their likelihood of success and their subjective valuation of academic tasks are shaped by individual, social, and cultural factors (Eccles & Wigfield, 2020).

Organization of the study

The reminder of this study is organized into five chapters and a bibliography in the following manner. Chapter 2 presents a review of the literature concerning the theoretical frameworks utilized at the study. Chapter 3 presents the research design and methodology of the study. Chapter 4 presents the results and findings. Chapter 5 contains a summary, conclusions, and recommendations of the study. The dissertation ends with a bibliography.

CHAPTER TWO: THEORETICAL FRAMEWORK

Chapter 2 of this dissertation presents the theoretical framework that underpins the research study. This chapter will explain three theoretical perspectives that are integrated and provide a consistent way of looking at the research problem. The theoretical frameworks are Models and Modeling Perspective, computational thinking, and cognitive engagement within Situated Expectancy Value Theory. These theories offer lenses through which I analyzed and interpreted the data collected in this study. My focus is on the cognitive engagement of women in STEM within Model Eliciting Activities in classroom settings.

My goal is to accumulate an all-encompassing comprehension of the relationship between students' cognitive engagement in eliciting computational thinking while working on a Model Eliciting Activity. The conceptual framework represents these perspectives distinctly and articulates how they interrelate, offering a coherent lens through which to inspect the research problem. This facilitates a more nuanced understanding of the complex phenomena at hand. This chapter provides an overview of each of these theories.

Previous research studies assessed computational thinking in a way that the men answering the tests had better results than the women (Román-González et al., 2018). However, other research studies show that there is no intellectual difference between men and women when performing activities in STEM (Riegle-Crumb, 2016). Riegle-Crumb points out that women and men perform similarly in math and science in early childhood, but women are less likely to pursue STEM fields in higher education and careers. Additionally, research studies have shown that women tend to have lower confidence in their math and science abilities than men, even when their actual performance is similar (Riegle-Crumb, 2016). Finally, the authors suggest that societal stereotypes and biases about gender roles and abilities may discourage women and women from pursuing STEM fields, even if they have the necessary skills and interest.

Models and Modeling Perspective (Lesh & Doerr, 2003) focuses on models as conceptual systems in which students engage in Model-Eliciting Activities (MEAs) involving explanatory systems functioning as models to interpret problem-solving situations. Computational thinking (CT), a fundamental problem-solving skill that every student should acquire to prepare them for higher technical skills, such as cybersecurity and cloud computing, as they continue in the STEM pipeline (Wing, 2006). Research studies have shown that computational thinking can improve problem-solving skills, as it involves breaking down complex problems into smaller, more manageable parts and developing algorithms to solve them (Wing, 2006). Cognitive engagement refers to the extent to which a student is mentally active and invested in the learning process. This concept is rooted in the Situated Expectancy Value Theory (SEVT), which suggests that students' cognitive engagement is shaped by their personal beliefs, goals, and values concerning education. According to the SEVT, students' level of cognitive engagement is determined by their perception of their capability to succeed (expectancy), combined with their personal interests and values related to the educational task (value). Hence, cognitive engagement can be seen as a fluctuating and context-dependent construct, affected by both personal traits and surrounding circumstances (Gladstone et al., 2022).

By combining these three frameworks, this study aims to explore how a well-designed MEA can create a learning environment to foster the cognitive engagement of women in the MEA and enhance their understanding of computational thinking to increase women's motivation to continue in STEM fields.

Models And Modeling Perspective

In mathematics education, models are often used to represent mathematical concepts, processes, and relationships. The term "modeling perspective" refers to the view that mathematical understanding involves not only knowledge of mathematical concepts and procedures but also the ability to create, use, and reflect upon mathematical models (Lesh & Doerr, 2003).

Model Eliciting Activities (MEAs) encourage gender equity by providing a learning environment that is tailored to a more diverse population than typical experiences. MEAs allow students with different backgrounds and values to emerge as talented problem-solvers (Alaprantis & Carmona, G., 2003). As students elicit their own understanding of the problem on their own meaningful and purposeful way, MEAs promote equitable learning. MEAs foster better participation and fairness by creating a classroom culture that values diverse perspectives and encourages active participation from all students (Clark et al., 2020; Lesh & Doerr, 2003; Zawojewski & Carmona, 2001).

MEAs are designed to engage students in solving complex, real-world problems that require teamwork, communication, and critical thinking skills, rather than just memorization of formulas or concepts. This approach helps to reduce the stereotype threat that women and other underrepresented groups often experience in traditional STEM courses. MEAs focus on collaboration and creativity rather than individual performance and competition, which can be particularly appealing to women who are more likely to value collaborative work (Diefes-Dux et al., 2004).

MEAs have been found to be effective in increasing diversity in STEM fields by addressing and assessing gender equity in the classroom. MEAs provide a means for students to work collaboratively on complex and real-world STEM problems, which can increase their interest and persistence. By focusing on collaboration and creativity rather than individual performance and competition, MEAs can provide a more welcoming and supportive learning environment for women and other underrepresented groups (Diefes-Dux et al., 2004).

According to the modeling perspective, students should be encouraged to engage in modeling activities that help them build a deeper understanding of STEM concepts and make connections between STEM ideas and real-world situations. By constructing and analyzing models, students can develop a more nuanced understanding of STEM and develop problem-solving and critical-thinking skills. They are different from open-ended problems because MEAs are specifically designed to prompt a problem-solving process that results in a specific problem (Hamilton, 2008; Hamilton & Lesh, 2008; Lesh & Doerr, 2003).

Lesh and Doerr (2003) explain how models and modeling perspective used to teach mathematics is at the intersection of education, psychology, and mathematics. This intersection is evident when we realize how after learning through models and modeling, students can communicate meaningfully with their parents, their community leaders, their teachers, and administrators and can understand policy and policymakers.

Models are conceptual systems where students engage in Model-Eliciting Activities (MEAs) that involve explanatory systems functioning as models in which students interpret problem-solving situations. These models were initially developed to facilitate the learning of conceptual models in mathematics and science education, allowing students to represent powerful ideas in real-life scenarios. Teacher educators and curriculum designers can use models and MEAs in STEM education (Lesh et al., 2003).

To comprehend the intersection discussed by scholars, it is essential to understand what a Model-Eliciting Activity (MEA) is and the benefits students receive from using MEAs in STEM education. MEAs are problem-solving activities that go beyond simple answers and require students to produce shareable, manipulative, and reusable conceptual tools. The focus of teachers utilizing MEAs is on the process students undertake to arrive at solutions, thereby eliciting their understanding of a particular subject (Hallström & Schönborn, 2019; Lesh & Doerr, 2003; Stohlmann, 2013).

MEAs are not lectures or lessons that yield a single answer, as there is no predetermined correct answer. Rather, MEAs represent a process through which students develop a model that presents a solution to a specific problem, as requested by a client. Models and modeling aid students in developing problem-solving skills, as well as prediction, decision-making, and communication skills (Gilbert & Boulter, 2012; Hallström & Schönborn, 2019).

Models and modeling are integral to interdisciplinary STEM education, as they serve as a bridge between STEM disciplines through authentic practices. They enhance STEM literacy by linking concepts and facilitating knowledge transfer across contexts. The benefit of models is that they focus on authentic STEM education by fostering interdisciplinary connections between subjects while preserving the integrity of each subject. Models and modeling, therefore, promote STEM education as a multidisciplinary approach to learning science, technology, engineering, and mathematics (Hamilton, 2008).

A crucial aspect to remember when discussing MEAs is that the process itself is the product. In a MEA, students engage in multiple iterations to find the best solution. During each iteration, students articulate the problem, test their hypotheses and potential solutions, and revise the models they have created to ensure that the model solves the problem at hand. MEAs are best performed over a minimum of two class periods with small teams of 3 to 5 students. The products generated from MEAs include descriptions, explanations, letters recommending specific solutions, discourse, or constructions. These products need to be shareable, transportable, and reusable. As students develop solutions, they are actively generalize concepts and higher-order thinking (Lesh & Doerr, 2003).

Model Eliciting Activities and Powerful Ideas

MEAs are symbolic representations of meaningful situations that provide teachers with a framework to facilitate the learning process for their students. MEAs are designed to simulate real-life problems, and students create artifacts as a result of their cognitive engagement with these activities. Students construct models that describe systems they encounter, making the learning experience purposeful and meaningful for them. When a student develops a model that is meaningful to them, they are effectively solving complex and powerful ideas. (Lesh et al., 2003)

When a conceptual system is expressed through various modes of representation, such as spoken language, written symbols, and concrete materials to simulate real-life situations, it becomes more powerful. This projection of internal systems to the external world helps students reach a level of representational fluency, indicating a deeper understanding of a conceptual system. According to Lesh and Doerr (2003), "In Model-Eliciting Activities, students make mathematical descriptions of meaningful situations."

Originally designed for teaching mathematics in meaningful contexts, MEAs have since been adopted for use in STEM education as well. The modeling cycle used in MEAs is the perfect framework to teach STEM. We start by a description of the problem, a real-life situation which makes it purposeful for students to learn. During this first step the teacher can give examples and explain situations in which we introduce the concept that we need the students to learn (Diefes-Dux et al., 2004; Hallström & Schönborn, 2019; Stohlmann, 2013).

The second step is the student's manipulation of the information and the tools that the teacher gives them to explore possible solutions. The students are given the opportunity to manipulate different materials and make use of their creativity to solve a specific problem. Once the group of students come up with a solution that in their group is the most efficient, then it is time for them to translate their knowledge and abstract to different situations. The cycle is closed with the verification of results; students assess if their solution was the best, if it is feasible, and if it solves the problem posted to them. This process is very much aligned with the engineering design process (Hamilton, 2008).

Students incorporate STEM concepts, simulating real-life scenarios. In addition, working in MEAs allows the students to deal with human constraints such as the different preferences of each team member, sets of values, and social dynamics. Adding STEM concepts and human constraints allows the students to enrich their knowledge and understanding of their environment, and of how things work in their communities and the world (Hamilton, 2008).

Models are based on systems that already exist and they focus on real-life situations that will help the student understand different concepts. MEA construct about world before word. Being important situations that are relevant to the students, it is easier to construct on their expertise and knowledge to come up with feasible and optimal solutions to different problems. The benefit of teaching STEM through models and modeling is that the entire process is a learning moment similar to what we experience in real-life situations. Students are able to develop ideas and constructs that explain systems they encounter (Lesh & Doerr, 2003).

MEAs are designed to lead significant forms of learning. Relevant objects that can be manipulated while working on the activities, relevant objects can be different artifacts and tools that the students find familiar and that they can use to symbolize the solution of a relevant problem inside the classroom. MEAs always consider relationships between teammates; the socio-cultural aspect of learning and teaching is a critical value in them.

As teachers and learners, when working in a Model-eliciting activity, we consider the actions the team takes, these actions that constitute processes are the product that results from the activity. Students understand patterns and regularities in the processes and are able to self-assess their results and decide whether or not they have a final solution or they need a new iteration to come up with better solutions(Baker & Galanti, 2017; Lesh & Doerr, 2003).

MEAs go through multiple modeling cycles that include a description of the problem, the manipulation of the model in which students generate predictions and the translation or the result of the prediction, the students are then able to give relevant results to the real world and finally, they will be able to verify the usefulness of their actions. After working on MEAs the students have a conceptual development; they modify their ways of thinking and provide foundations for big ideas.

Working through a MEA, students are supposed to mathematize a real-life problem; the theory presents the different results students might obtain after working in MEAs. Students can quantify, dimensionalize, coordinate, categorize, algebratize, and systematize concepts presented to them. During the MEA, the constructs themselves need to be processed. Students can adapt, modify, and refine ideas that they have (Lesh & Doerr, 2003).

Models and modeling encourage students' development of constructs that are formal abstractions used in meaningful situations. Models and modeling elicit understanding of concepts by putting students in familiar situations that help them clearly understand the problems and situations presented. Students' responses are constructed from their everyday knowledge and experiences.

MEAs operationalize knowledge as students understand and create constructs. While observing students during the development of a MEA, teachers can see more detailed answers to the problems presented. MEAs help students coordinate relevant systems into stable conceptual systems. MEAs put students in situations they can solve with their tools and knowledge; they are able to reveal concepts that they later test and refine with alternative ways of thinking. The conceptual models' students develop constructs or conceptual systems and produce artifacts or representational media.

Models and modeling can help students develop 21st-century skills. Students need to develop mathematical skills that will prepare them to solve real-life problems. The skills they develop will help them become more successful in the workforce that has been steadily changing. Students with the capacity to innovate, adapt, communicate, and synthesize information will be more likely to succeed in the workforce. MEAs combine teaching concepts while developing 21st-century skills (Hallström & Schönborn, 2019).

Six Principles of MEAs.

MEAs are developed keeping in mind six principles that secure the generation of knowledge and powerful ideas.

1. Personal Meaningfulness Principle, the students should be encouraged to understand a situation and use their personal knowledge and experience to solve problems. It is essential that students are considered and have the opportunity to participate and

express their point of view, not being forced to conform to the teacher's point of view of the solution and the problem.

2. The Model Construction Principle. Well-designed MEAs need to make sure the tasks allow the students to clearly recognize there is a need for the creation, modification, extension, or refinement of a model. The task will encourage students to manipulate, explain or describe a significant system. The focus of the MEAs should be on underlying abstraction and pattern recognition instead of superficial answers to the problems.
3. The Self-evaluation Principle. The students need to clearly understand the criteria and the definition of success for the problem so they can assess the usefulness of alternative responses. Students will be able to perform a self-assessment that will allow them to judge their responses and results. A key aspect of MEAs is that they involve an iterative process, and the best solution is not necessarily the first solution the team comes up with.
4. The Model-externalization principle. During the design of the Model-eliciting activities, the teacher needs to make sure students reveal how they are solving the situation and the type of system that they are thinking about. The artifacts and process must reveal the process taken to reach such results.
5. The Simple Prototype Principle. Simple situations that require significant models. The situations presented in MEAs do not have to be complex; simple situations will help students understand complex problems and create significant models. The solution or prototype presented will be useful in different situations. The activity will

provide explanatory power that will help students make sense of structurally similar situations.

6. The Model Generalization Principle. The conceptual tools generated during a Model-Eliciting Activity not only apply to the problem presented, but they can also be generalized and can be easily adapted to a broader range of situations. The challenge is to produce results that are sharable, reusable, and modifiable models. Students should be able to generalize what they learned.

Guided by these six principles, Model-Eliciting Activities foster students' creativity and intelligence, key components of 21st-century learners. Students will be able to innovate and solve problems beyond conventional ways. MEAs help students synthesize information and recognize information that is relevant and worth pursuing to solve the problems posted. They will be able to communicate with peers; they will develop the ability to convince others and convey the value of their ideas. The way MEAs are operationalized will help students adapt to different points of view; in each iteration of the problem, students will be presented with new constraints and ideas that they will be able to incorporate into their process and results (Lesh & Doerr, 2003).

Equity with Models and Modeling Perspective

According to Lesh (2003), models and modeling perspectives can promote equity in STEM education by providing a framework that is accessible and inclusive for women and all students, regardless of their gender, cultural or socioeconomic background. This is because modeling emphasizes the use of multiple representations, such as diagrams, graphs, and simulations, to represent complex systems and phenomena in ways that are accessible to a wide range of learners.

Research studies have shown that using models and modeling perspectives can help to engage and motivate students who may have been previously disinterested in STEM subjects (National Research Council, 2012). By providing a visual and interactive means of exploring complex concepts, models and modeling perspectives can help to overcome some of the traditional barriers to learning in STEM, such as language barriers or limited prior knowledge.

Furthermore, models and modeling perspectives can also help to promote diversity and inclusion in STEM education by highlighting the ways in which STEM knowledge is socially constructed and situated within particular cultural contexts. This can help to challenge stereotypes and promote a more inclusive and equitable learning environment (Barton & Tan, 2020).

In conclusion, Lesh (2003) argues that models and modeling perspectives can play an important role in promoting equity in STEM education by providing a more inclusive and accessible framework for learning. By emphasizing the use of multiple representations and highlighting the socially constructed nature of STEM knowledge, models and modeling perspectives can help to engage and motivate a wider range of learners and promote a more diverse and inclusive learning environment.

Computational Thinking

Definition

In early 2000, Professor Dr. Jeannette M. Wing from Carnegie Mellon introduced the concept of computational Thinking. She defined it as a fundamental skill that enables individuals to solve problems, design systems, and understand human behavior by using a set of mental tools that are based on computer science concepts. With the help of computational thinking, individuals can reformulate complex problems into more manageable ones that can be solved.

Wing emphasized that computational thinking is not just a set of technical skills but also a set of attitudes and skills that are necessary for problem-solving (Wing, 2006).

> *Computational thinking is the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent. (Cuny et al., 2010)*

Before Wing, Papert also mentioned CT in the context of computationally based mathematics education. Papert defined CT as how computers can help solve problems by "forging ideas" and allowing analysis and explanation of problems, solutions, and the connections between them. This highlights the idea that CT is not just limited to computer science and can be applied to various fields and industries (Papert, 1980).

Computational thinking (CT) is a fundamental skill that enables students to solve problems, design systems, and understand human behavior using the mental tools of computer science. CT involves the use of mental tools to solve problems, design systems, and understand human behavior at multiple levels of abstraction. This high-level thought process allows individuals to understand essential properties of common objects and to implement abstractions while working within constraints (Amri et al., 2019; Grover & Pea, 2013; Wing, 2006).

Shute (2017) defines CT as a skill that can be applied to both well-structured and ill-structured problems, meaning it can be used to solve real-life problems with solutions that may not have definite or measurable outcomes. CT also encourages problem-solving skills, confidence, and persistence (Barr et al., 2011) and the ability to think with the computer as a tool (Berland & Wilensky, 2015), which can improve problem-solving skills, communication, and computational content, and increase interest in STEM careers. Wing (2008) argues that computational thinking is not thinking like a computer, but engaging in cognitive processes that help students solve problems.

As our world has evolved, the ability to effectively harness the power of computers has become increasingly important. CT is a vital skill for success in the 21st century because it enables individuals to navigate and understand the complex systems that make up our world. It involves using a systematic problem-solving approach that includes breaking down complex problems into smaller, manageable parts, analyzing and understanding these parts, and then translating them into a form that technology can understand to create solutions(Amri et al., 2019; Cuny et al., 2010).

Computational thinking involves using technology to create a solution, including computer programming, algorithms, and other forms of digital technology, to create an efficient, effective, and accurate solution. It also involves the ability to test and debug a solution and the ability to adapt and modify the solution as necessary. Additionally, it develops confidence, persistence to solve complex tasks, and efficient teamwork (Barr et al., 2011).

The National Research Council (2010) emphasizes the importance of teaching computational thinking as a fundamental skill for all students, regardless of their future career paths. This is supported by the inclusion of computational thinking as one of the eight core scientific practices in the Next Generation Science Standards (NGSS). CT is a cognitive process that builds on the power and limits of computing processes. It helps individuals to solve problems, design systems, and understand human behavior by thinking recursively, parallel processing, and recognizing the virtues and dangers of any activity.

The purpose of computational thinking is to design for simplicity and elegance of the system. By using this skill, individuals are able to break down complex problems into smaller, manageable parts and develop efficient solutions. They also learn to think about the problem from different perspectives, which allows them to consider alternative solutions and identify potential areas of improvement. Additionally, the use of computational thinking allows individuals to understand the potential consequences of their decisions and how these decisions may impact the system as a whole (Caeli & Yadav, 2020).

The result of computational thinking is the ability to understand and use concepts and constructs that are relevant to a given problem or system. This understanding is achieved through the process of creating models, which are simplified representations of complex systems used to explain or predict their behavior. By using computational thinking, individuals can gain a deeper understanding of the systems they are studying and are able to effectively use and communicate with technology (Shute et al., 2017).

In summary, computational thinking is a cognitive process that aims to generate ideas and understanding of concepts and constructs through the process of creating models. This process is essential for problem-solving, managing daily life, communication, and interaction with others in various fields. It is increasingly recognized as a crucial skill for success in the digital age, as it enables individuals to navigate complex systems and effectively harness the power of computers.

Computational thinking can help women develop an interest in STEM fields. Results from research studies have shown that women who are exposed to computational thinking at a young age are more likely to develop an interest in STEM fields (Weintrop et al., 2016). By providing opportunities for women to engage in computational thinking activities, educators and parents can help to promote interest and engagement in STEM fields. Research studies have shown that women who engage in computational thinking activities develop a sense of agency and empowerment as they learn to solve problems and create projects on their own (Kafai &

Burke, 2014). This can help to boost women's confidence and self-esteem, which can be especially valuable in fields where CT is used, where women are underrepresented. In Weintrop et al. (2016) the results of the study indicate that the integration of computational thinking material into STEM classes may result in enhanced self-assurance and attitudes in women students, with no discernible aptitude disparity between genders.

Taxonomy of Computational Thinking

Computational thinking is a cognitive process that is characterized by several key elements. One of the most important of these elements is conceptualizing or understanding concepts. This involves the ability to identify and understand the underlying principles and ideas that are relevant to a given problem or system.

Another important aspect of computational thinking is abstraction. This is a fundamental skill that is essential for problem-solving and is an integral part of human cognition. Abstraction allows individuals to simplify complex problems and systems by identifying the most essential elements and disregarding unnecessary details.

It is important to note that computational thinking is not an attempt to get humans to think like computers, but rather to be clever and imaginative. It complements and combines mathematical and engineering thinking to provide individuals with a powerful tool for understanding and solving complex problems. Computational thinking is a skill that is becoming increasingly important in today's world, as technology continues to advance and become more pervasive.

The taxonomy of computational thinking developed by Wing (2006) includes the following elements: problem reformulation, recursion, problem decomposition, abstraction, and systematic testing. These elements are used to operationalize and classify the different aspects of computational thinking, making it easier to understand and organize. Other researchers have also developed their own taxonomies of computational thinking, which may include different or additional elements. By comparing the skills or processes of computational thinking as described in various taxonomies, it is possible to gain a deeper understanding of how students use computational thinking to solve problems and analyze their conversations. Table 1 will help us illustrate the different categories some of the authors in computational thinking provide.

Table 1

Taxonomy Comparison

Wing (2006)	Problem decomposition: break to manageable units.	Recursion: construct incrementally based on previous information.	Abstraction: model core aspects of complex problems.	Problem reformulation: reframe into a solvable problem.	Systematic testing: Purposeful actions to get solutions.
National Research Council (2010)	Hypothesis testing: understand how the system works	Data management: gathering data, processing data patterns, and representing data in a meaningful way.	Parallelism: process information from multiple sources.	Abstraction: modeling workings of complex problems.	Debugging: Finding and fixing errors.
Krauss & Prottsman (2016)	Decomposition: breaking problems down into smaller parts.	Pattern recognition: finding similarities between items	Abstraction: removing details for generalization.	Algorithm: automating the processes by designing a sequence of logical instructions.	
Anderson (2016)	Problem decomposition.	Pattern recognition.	Abstraction.	Algorithm design for solutions.	Evaluation of solutions.

For this study, I will utilize (Krauss & Prottsman, 2016) taxonomy as it provides a lucid insight into how high school students and their teachers interpret and perceive computational thinking.

The first key element of computational thinking is the ability to decompose a problem into smaller, more manageable sub-problems that can be solved independently: decomposition. This allows for a more efficient and effective solution to the problem, as well as a better understanding of the problem itself. For example, in a robotics project, decomposition would involve breaking down the task of building a robot into smaller tasks, such as designing the robot's frame, programming its movements, and testing its functionality (Krauss & Prottsman, 2016).

The second key element of CT is pattern recognition, which involves identifying patterns and regularities in data or problem situations. This includes identifying the key elements of a problem, understanding the relationships between those elements, and determining the most appropriate solution. This requires a systematic and logical approach to problem-solving, as well as the ability to think critically and creatively. For example, in a data analysis project, pattern recognition would involve identifying patterns in data sets and using those patterns to make predictions or decisions (Krauss & Prottsman, 2016).

Abstraction is the third key element of CT; it involves creating simplified models or representations of a problem or system. This allows for a better understanding of the problem and its underlying principles, as well as a more efficient solution. For example, in a computer programming project, abstraction would involve creating a simplified model of the problem to understand the problem better and develop a solution (Krauss & Prottsman, 2016).

The process of abstraction involves deciding which details to consider and which to ignore, allowing individuals to scale and deal with complex systems. It also allows for a layered architecture, where the relationship between layers can be mapped and the implementation of software does not require knowledge of all potential users. Computing is the automation of abstraction, and computational thinking does not require a machine.

By using abstraction layers or hierarchical decomposition, individuals can model complex systems and identify tipping points and emergent behaviors. They can also validate models against the truth. This deeper level of computational thinking allows for the analysis of big data and the running of simulations of complex systems, ultimately leading to a better understanding of the knowledge embedded in the data (Wing, 2008).

Algorithm design is the fourth key element of CT, which involves creating a step-by-step process to solve a problem. This includes using computer programming, algorithms, and other forms of digital technology to create a solution that is efficient, effective, and accurate. It also involves the ability to test and debug a solution, as well as the ability to adapt and modify the solution as necessary. For example, in a web development project, algorithm design would involve creating a step-by-step process for designing and building a website (Krauss & Prottsman, 2016; Wing, 2008).

Evaluation is the last aspect of CT; it involves testing and evaluating a solution to ensure it is effective and efficient. This includes testing the solution against the problem it was designed to solve, evaluating its performance, and making any necessary modifications. For example, in a software development project, the evaluation would involve testing the software to ensure it is free of bugs and meets the users' needs (Wing, 2008).

Computational Thinking and Other Disciplines

Computational thinking is a multidisciplinary approach that combines mathematical and engineering thinking, analytical thinking, and scientific thinking. This approach incorporates foundational mathematics to build systems that can interact effectively. Analytical thinking, which includes the ability to use mathematics to solve problems, is a fundamental component of this approach. Engineering, which involves the design and evaluation of complex systems with constraints, is also a crucial aspect of computational thinking. Additionally, scientific thinking, or the methodology of understanding, plays a vital role in this approach. Overall, computational thinking represents a holistic approach to the design, evaluation, and understanding of complex systems (Barr et al., 2011; Berland & Wilensky, 2015; Weintrop et al., 2016).

Computational thinking is a cognitive process that encompasses several key elements, including logical and systems thinking, algorithmic thinking, and parallel thinking. This type of thinking involves various thought processes, such as compositional reasoning, pattern matching, procedural thinking, and recursive thinking. These elements work together to enable individuals to solve problems and understand complex systems using computational approaches.

Solving problems utilizing computational thinking entails several key characteristics, one of which is the utilization of abstraction and decomposition when addressing a large and complex task. This approach enables students to simplify the problem by identifying the essential elements and disregarding unnecessary details. This process of abstraction is fundamental for problem-solving, as it allows individuals to focus on the crucial aspects of the problem and develop an efficient solution (Ching et al., 2018).

Another characteristic of solving problems using computational thinking is the capacity to reformulate challenging problems. This requires individuals to consider the problem from different perspectives, which allows them to evaluate alternative solutions and identify potential areas of improvement.

Once students have a comprehensive understanding of how to solve the problem, they can apply reduction, embedding, transformation, or simulation methods. These methods enable them to take the understanding of the problem and its solution and apply it to different scenarios. Reduction simplifies the problem, embedding allows for solving the problem in a different context, transformation modifies the problem, and simulation tests the problem and its solution.

In conclusion, solving problems utilizing computational thinking involves several key characteristics, including using abstraction and decomposition, the capacity to reformulate challenging problems, and applying reduction, embedding, transformation, or simulation methods once the solution is understood. These characteristics allow students to tackle large and complex problems efficiently and effectively.

Situated Expectancy Value Theory

The Situated Expectancy Value Theory (SEVT) serves as a theoretical blueprint that elucidates individuals' educational and career choice rationales. According to SEVT, decisions are driven by individuals' self-perceptions of their capacities (self-efficacy), the significance they attach to a specific activity or subject (task value), and their success prospects within that realm (outcome expectations) (Eccles & Wigfield, 2020b).

Eccles (2007) explains that women's outcome expectations in STEM fields are often lower than men's, which can discourage the former from pursuing STEM careers. For instance, a study by Eccles (2007) found that women who perceived a lower chance of success in math and science courses, during high school, were less likely to pursue STEM fields in college. Situated Expectancy-Value Theory (SEVT) offers a valuable framework for understanding the complex factors that influence women's engagement in classroom setting that will develop in higher expectancy of success. Situated Expectancy Value Theory (SEVT) is a theoretical framework that emphasizes the contextual and situational factors that influence students' motivation and cognitive engagement in academic activities. SEVT posits that students' motivation and cognitive engagement are shaped by their expectations about the difficulty and relevance of the task, as well as their personal values and goals related to the task.

Situated expectancy-value theory offers a useful framework for understanding the factors that influence women's cognitive engagement in STEM in the classroom. Research studies have shown that women's beliefs about their ability to succeed in STEM activities are influenced by a variety of factors, including their prior experiences, feedback from others, and their perceptions of the social and cultural context (Eccles, 2016; Eccles & Wang, 2016). Additionally, women's subjective valuation of STEM activities is shaped by their personal interests, values, and goals.

When applied to the classroom context, situated expectancy-value theory suggests that efforts to promote women's participation in STEM should focus on creating an environment that promotes positive beliefs and values related to STEM activities. This might involve providing opportunities for women to engage in STEM activities that are personally meaningful and relevant to their goals and interests, as well as providing positive feedback and recognition for their efforts (Murphy & Dweck, 2010). Additionally, efforts to reduce stereotype threat and promote positive attitudes towards women in STEM can help to create a more supportive and inclusive classroom environment (Spencer et al., 1999).

Students' expectations and values are influenced by their beliefs, task difficulty, goals, identities, and affective memories of different events. These beliefs, goals, and memories are influenced by the perception of other people's attitudes and expectations of them. Social and cultural factors influence these perceptions.

The model should consider that some of the students' choices are unconscious. Students are only sometimes aware of the influences they have based on socialization and culture. The processes in the model are dynamic, situationally sensitive, and phenomenological; they are not static.

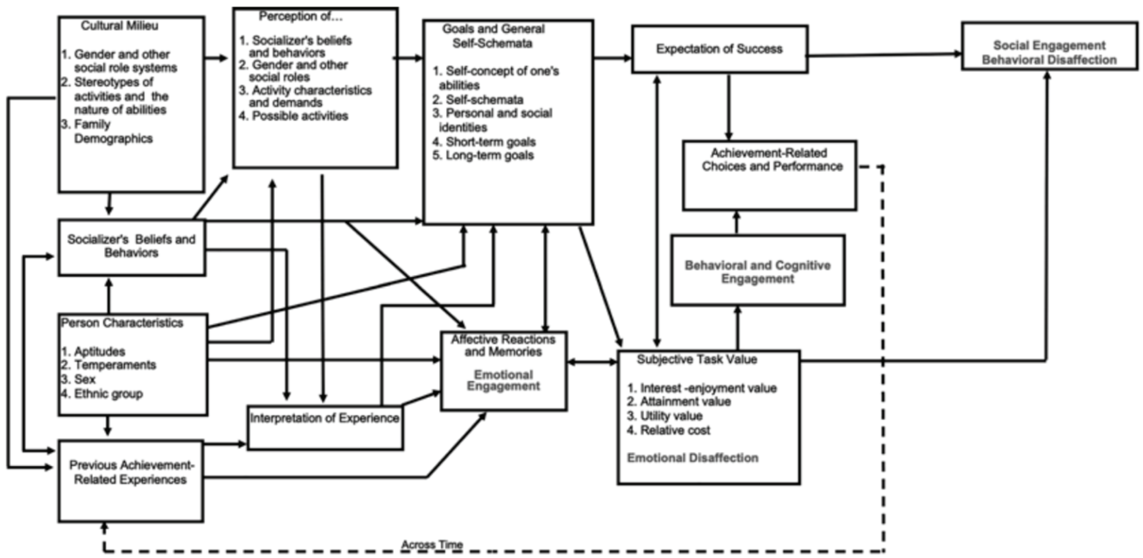

Figure 2

Gladstone's Engagement in SEVT Model

Note: From "Situated Expectancy-Value Theory, Dimensions of Engagement, and Academic Outcomes" by J. R. Gladstone, A. Wigfield, and J.S. Eccles, 2022, *Handbook of Research on Student Engagement*, pp.70, Copyright 2022.

Figure 2 is the adaptation of Gladstone as we can see in the diagram, social engagement depends on the expectation of success and the subjective task value (the value students give to activities or classes). Engagement is a precursor for academic outcomes. Students who are engaged in learning are more likely to persist in challenging tasks.

According to this theory, cognitive engagement is a critical component of achievement, as it drives individuals to persist in challenging tasks and fosters the development of their abilities. In the context of women in STEM, cognitive engagement is a critical factor in understanding their underrepresentation in these fields. Women may not engage in STEM activities to the same extent as men due to a variety of factors, such as negative experiences in STEM courses (Gladstone et al., 2022).

Research studies have shown that women who are more cognitively engaged in STEM are more likely to persist in these fields and overcome the barriers that may hinder their success. For example, a study by Fouad et al. (2016) found that women who had higher levels of STEM cognitive engagement were more likely to choose STEM majors in college and were more likely to persist in these majors. Similarly, a study by Good et al. (2012) found that women who had higher levels of cognitive engagement in STEM were more likely to persist in STEM careers.

Cognitive engagement in STEM can be fostered by creating environments that support women's beliefs about their abilities and the value of STEM fields. This can include providing female role models, offering opportunities for hands-on learning, and creating supportive communities. Cognitive engagement is a critical factor in understanding the underrepresentation of women in STEM fields. The Situated Expectancy Value Theory framework provides a useful lens through which to understand how cognitive engagement is influenced by individual beliefs and contextual factors. Creating environments that foster cognitive engagement may be a key strategy for promoting women's success in STEM fields.

The dimensions of engagement can promote positive student outcomes: achievement, course intentions, and well-being. Gladstone incorporated engagement in the SEVT framework. There is no learning without cognitive engagement (Chen, 2013). Research studies suggest that cognitive engagement is influenced by the students' self- evaluation and perceived value in the activities presented.

Research studies have shown that cognitive engagement and motivation are crucial for success in STEM fields, particularly for women who face unique challenges and barriers in these disciplines (Eccles & Wang, 2016; National Science Foundation, 2019). The situated expectancy-value theory provides a useful framework for understanding and measuring cognitive engagement among women in STEM (Wang & Degol, 2017). Women in STEM fields may have lower expectancy beliefs and less value placed on STEM tasks due to negative stereotypes and societal expectations that they are less capable in these fields than their male counterparts (Eccles & Wang, 2016). Measuring cognitive engagement among women in STEM can provide valuable insights into the factors that influence their success in these fields (Fredricks, Jennifer & McColskey, Wendy, 2012; Wang & Degol, 2017).

Gladstone (2022) identifies engagement and motivation as critical factors for achieving positive outcomes for women in STEM fields. To support the success of women in STEM, educators, and policymakers must understand and measure these factors and create supportive environments that foster cognitive engagement and motivation. The influence of motivation on performance and decision-making underscores its importance. Gladstone describes four dimensions of student engagement: behavioral, emotional, agentic, and social engagement. This study will focus specifically on cognitive engagement, which aligns with the purpose of Model Eliciting Activities, to be discussed later in this chapter.

According to Gladstone, Wigfield, and Eccles (2022), cognitive engagement is the degree to which a student is actively and cognitively involved in learning. This concept is grounded in the Situated Expectancy Value Theory (EVT), which suggests that students' cognitive engagement is influenced by their beliefs, values, and goals related to learning. EVT proposes that students' perceptions of their ability to succeed (expectancy) and their values and interests in the learning task (value) interact to determine their level of cognitive engagement. In this way, cognitive engagement can be understood as a dynamic and situated construct influenced by individual and contextual factors.

Cognitive engagement can be measured by the students' self-regulation, strategy use, goal setting, and exerting effort. (Appleton et al., 2006; Connell & Wellborn, 1991; Corno & Mandinach, 1983; Meece et al., 1988). Cognitive engagement was defined as students using cognitive strategies, self-regulation, and exerting mental effort. Further conceptualized cognitive engagement by contrasting deep versus shallow cognitive engagement (Gladstone et al., 2022).

Cognitive engagement can be measured by the frequency of high-level evaluation, questions, authentic questions, and uptake (evidence that subsequent answers are incorporated). Other indicators of cognitive engagement are self-monitoring, exchanging ideas, giving directions, and justifying answers (Fredricks, Jennifer & McColskey, Wendy, 2012).

Definitions by Gladstone on Cognitive Engagement:

- Self-Regulation. According to Eccles and Wigfield (2002), refers to the process through which individuals actively monitor and control their thoughts, feelings, and behaviors in order to achieve their goals. This includes setting goals, planning and organizing one's time and resources, monitoring progress, and adapting strategies as needed. Self-regulation also involves the ability to regulate one's emotions and motivation, to persist in the face of obstacles and setbacks, and to self-evaluate one's progress towards achieving the goal. Overall, self-regulation is seen as a critical component of achievement motivation, as it allows individuals to direct their efforts towards meaningful goals and to adjust their behavior as needed in order to achieve those goals.
- Exchanging ideas. Process of sharing and discussing ideas, perspectives, and insights with others. More specifically, exchanging ideas involves the communication of thoughts

and concepts among individuals or groups to build mutual understanding, increase knowledge, and generate new insights. This exchange can take many forms, including discussions, debates, brainstorming sessions, and collaborative problem-solving activities. In the context of motivation and learning, exchanging ideas can be particularly valuable as it can help individuals to clarify their own beliefs and goals, challenge and refine their understanding, and learn from the experiences and perspectives of others. Through this process, individuals can gain a deeper appreciation of the complexity of the learning process and develop new strategies and approaches to enhance their motivation and performance.

- Giving directions. Providing guidance or instructions to individuals to help them achieve their goals. More specifically, giving directions involves communicating specific steps, strategies, or actions that individuals can take to move toward their desired outcome. These directions can be provided in a variety of formats, such as verbal instructions, written guidelines, or visual aids. In the context of motivation and learning, giving directions can be an important part of helping individuals to understand what is expected of them and how they can best achieve their goals. Clear and concise directions can provide individuals with a sense of structure and direction and help them to feel more confident and competent in their abilities. However, it is important to note that giving directions is just one part of the motivation and learning process, and that individuals also need to be able to set their own goals, make choices, and take ownership of their learning to be truly motivated and successful.
- Justifying answers. The process of providing evidence or reasons to support a particular response or solution to a problem. More specifically, justifying answers involves

explaining why a particular response or solution is valid or appropriate, using logical reasoning and relevant evidence. This process of justification requires individuals to think critically and reflect on their own thinking, as well as consider alternative perspectives or solutions. In the context of motivation and learning, justifying answers is an important skill for individuals to develop as it can help them to understand and articulate their own thought processes, evaluate the quality of their own and others' reasoning, and engage in productive discussion and debate. By justifying their answers, individuals can also develop a deeper understanding of the concepts and ideas they are learning and become more confident in their ability to apply these concepts in new and unfamiliar situations. Overall, justifying answers is an important part of the learning process as it promotes critical thinking, reflection, and the development of deeper understanding and knowledge.

- <u>Asking questions</u>. The process of seeking information, clarifying understanding, and exploring ideas through inquiry. More specifically, asking questions involves actively seeking out information, insights, and perspectives through inquiry, either by posing questions to oneself or to others. This process of questioning requires individuals to engage in critical thinking and reflection, as well as demonstrate curiosity and a willingness to learn. In the context of motivation and learning, asking questions is an important skill for individuals to develop as it can help them to clarify their understanding, identify gaps in their knowledge, and generate new insights and ideas. By asking questions, individuals can also deepen their cognitive engagement with the material they are learning and develop a more nuanced and sophisticated understanding of complex concepts. Moreover, asking questions can foster a more collaborative and interactive learning environment, where individuals can engage in discussion and debate, share their ideas and perspectives, and build on each other's knowledge and understanding. Overall, asking questions is an essential part of the learning process, as it promotes curiosity, critical thinking, and the development of deeper understanding and knowledge.

- Uptake. The process of taking in or internalizing new information, ideas, or skills. More specifically, uptake involves actively engaging with new information or ideas, making connections between new and existing knowledge, and integrating new insights or skills into one's existing mental framework. This process of uptake requires individuals to actively process and synthesize new information, as well as engage in self-reflection and self-evaluation to assess their own understanding and progress. In the context of motivation and learning, uptake is an important component of the learning process as it allows individuals to build upon their existing knowledge and develop new skills and competencies. Effective uptake involves not only acquiring new knowledge or skills, but also making meaningful connections between different pieces of information and applying new insights or skills in real-world contexts. Moreover, effective uptake is often linked to intrinsic motivation, as individuals who are highly motivated to learn are more likely to actively engage with new information and ideas and take ownership of their own learning process. Overall, uptake is an essential part of the learning process, as it promotes deep understanding, skill development, and the ability to apply new knowledge in meaningful ways.

CHAPTER THREE: METHOD AND RESEARCH DESIGN

Introduction

In this chapter, I describe the methodology that was used to explore the extent to which women are engaged in open-ended modeling activities, particularly in relation to computational thinking and the factors that may affect their level of involvement in these STEM-related tasks. The dimensions of engagement can promote positive student outcomes: achievement, course intentions, and well-being. Student engagement is comprised of three dimensions: behavioral, cognitive, and emotional engagement (Gladstone et al., 2022). In this study I focused on cognitive engagement of a team of women eliciting computational thinking while collaborating on the Tic-tac-toe model-eliciting activity (MEA) (Carmona et al., 2021). I then compared similarities and differences with a team of men solving the same activity.

Computational thinking is a skill that every student should learn, and that increases their likelihood of success when learning more advanced technical skills; and it is essential for future success in STEM fields (Zawojewski & Carmona, 2001). This chapter provides an overview of the research design, participants, data collection procedures, and data analysis methods used to address the research questions. An essential component of this study's research methodology involved analyzing student discussions, with an emphasis on uncovering any discernible differences in cognitive engagement and elicitation of computational thinking between men and women. The lens used for this analysis was the Situated Expectancy Value Theory (Eccles & Wigfield, 2020a), a framework that provides insightful perspectives on engagement, taking into account factors such as individual beliefs, values, and learning goals within the context of each student's situation. Models and modeling perspectives have shown to encourage student participation and promote equitable learning opportunities (Lesh & Doerr, 2003).

The study was conducted in a high school in South Texas during a Cybersecurity class, students enrolled were sophomores, juniors and seniors. The students were given a Model Eliciting Activity in which they had to come up with an algorithm that showed the computer how to win a Tic-tac-toe game every time it played. Students were divided into two different comparison groups in which there is an explicit number of men and women on each team (one team of only men, one team of only women). With these teams I could analyze the conversations between team members and compare them in terms of computational thinking categories and Cognitive Engagement characteristics.

As stated in the previous chapter, I sought to examine women's and men's cognitive engagement while solving a Model Eliciting Activity that elicits computational thinking (Galarza-Tohen et al., 2023) and the similarities and differences between the groups.

This chapter outlines the research questions, objectives, and methodology that were employed to achieve these goals. The study contributes to the current understanding of gender and diversity issues in STEM education and informs ways to promote women's cognitive engagement and success in these fields.

The findings of this study can be of significant value to educators, policymakers, and other stakeholders who are interested in promoting greater diversity and equity in STEM and cybersecurity fields. Specifically, the study contributes to the development of more effective strategies for engaging and retaining women in these fields, ultimately leading to greater representation and diversity in the cybersecurity workforce.

Purpose Statement, Hypotheses, and Research Questions

Purpose Statement

This study proposes to examine women's and men's cognitive engagement in a Model Eliciting Activity (MEA) that elicits computational thinking, analyzing the relationship between cognitive engagement and CT for women and men.

Hypothesis

I hypothesized that when provided with a learning environment, such as a Model Eliciting Activity in which students are encouraged to participate in a way that is meaningful and purposeful for them, they cognitively engage and therefore increase their motivation and later on their expectancy of success. Previous research studies tell us that women are more likely to understand and be motivated when taught in a purposeful and meaningful way, that is, within their social context (Tang et al., 2020).

Research questions:

- **RQ1**. How does student cognitive engagement relate to computational thinking while solving the Tic-tac-toe MEA?
- **RQ2.** What are similarities and distinctions between the two teams, depending on team members' gender (one all-women team and one all-men team)?

Research Design

To this end Epistemic Network Analysis (Shaffer & Ruis, 2017) was utilized. Analyzing the conversations helped me understand the difference between women and men in how each student cognitively engages in the activity and elicits CT.

ENA is used to examine the connections and uses visualization and statistical techniques to identify patterns, and quantifies the co-occurrence of concepts within a conversation (Bowman et al., 2021; Shaffer, 2017). By using ENA, I was able to uncover the relationship between student cognitive engagement and computational thinking. Moreover, using subtracted network analysis, I was able to compare and identify differences in the relationship between student cognitive engagement and computational thinking.

Epistemic Network Analysis

In order to run the Epistemic Network Analysis tool so I could understand how computational thinking is elicited and how women and men cognitively engage in the activities, the conversations of the students throughout their learning process had to be classified and coded. MEAs are purposefully designed to elicit students thinking as they develop meaningful concepts, such as computational thinking. Thus, analyzing students discourse as students engage in the process of eliciting computational thinking when solving an MEA allows us to better understand its epistemic nature.

The conversations were constructed in a manner that upheld the context and situated meaning of each interaction. The research design centered on examining the utterances of conversation present in transcripts of video recordings of students working on an MEA, with the aim of exploring patterns and co-occurrences of the coded constructs in the conversations. To achieve this, I used Epistemic Network Analysis (Shaffer, 2017).

Epistemic Network Analysis is a methodology that helps to identify patterns and relationships within social networks and how they impact the flow of knowledge and ideas. By using this analysis, the study was able to uncover the different ways in which students engaged in the teams and how they elicited computational thinking. By having different team conformations based on student gender, this study provides important insights into the gender disparities in the field of computational thinking and provides valuable information for educators and policymakers who seek to promote greater gender equity in STEM fields (Shaffer et al., 2016).

Quantitative ethnography uses statistical techniques to increase the scope and power of ethnographic or other qualitative methods (Shaffer, 2017). It combines statistical inference with qualitative analysis. It respects the insights gained by ethnography and applies the power of statistical techniques (Shaffer et al., 2009). Epistemic network analysis (ENA) is a tool used in quantitative ethnography that can be used for discourse analysis. It models the association between elements of complex thinking and models cognitive networks by analyzing the connections among cognitive elements rather than in isolation.

Epistemic network analysis (ENA) is a method for the analysis of networks. ENA models cognitive networks since 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 (Buckingham Shum et al., 2019; Shaffer et al., 2016; A. Siebert-Evenstone & Shaffer, 2019). With ENA, we can understand meaningful connections among the participants and focus on the quality of the connections rather than on the number of instances (Bressler et al., 2019; Shaffer, 2017; Shaffer et al., 2009).

In an ENA network the thickness of line is the strength of the relationship between the concepts (Marquart, C. L., Hinojosa, C., Swiecki, Z., Eagan, B., & Shaffer, D. W., 2018). For this study, I analyzed the conversation between students (Arastoopour et al., 2015; Eagan & Hamilton, 2018).

ENA can also construct a subtracted network, subtracting the weight of the connections from two networks and highlighting the difference between the participants. The subtracted network is a mathematically visual representation of the differences between the nets, the program subtracts the number of co-occurrences between the teams to get a new plot in which we visualize which team made more connections for certain codes. The darker and thicker lines are the result of greater differences, lighter lines indicate that there are no great differences between the network. The color of the lines depends on the network that has the stronger connection (Shaffer et al., 2016).

ENA tool fixes the node positions for the analysis of the network. This means the nodes will be in the same place even if we analyze different participants or parts of the conversation; this gives us the opportunity to compare and analyze data. By using ENA, I was able to uncover the relationship between student cognitive engagement and computational thinking for each team.

I analyzed the conversations, with co-occurrences for each category and characteristic, defining the patterns of the conversations and the subtracted networks to understand the differences. Knowing that students elicit computational thinking and engage in an activity in different ways (Galarza-Tohen et al., 2023) helps understand gender differences and expectancies of women and men in the classroom.

ENA measures the co-occurrences of connections between constructs or codes, whereby the frequency of their co-occurrence determines the intensity of the association between two constructs in the discourse. It is crucial to partition the data into coherent and substantive units. In this study, the data was partitioned according to the participations during the conversation, one utterance corresponds to one line of conversation. During this study, I divided the data by interventions of the participants in the team and analyzed the co-occurrences of connections in the for a window stanza of 20. In the context of Epistemic Network Analysis (ENA), a "window stanza" refers to a segment of text that contains a meaningful unit of information for the analysis, typically spanning four sentences.

In this study, it was preferable to analyze twenty lines rather than a small window stanza of just four lines of conversation. This is because the meaning of individual statements can be heavily influenced by the context in which they are situated. Analyzing only a small window of conversation can therefore result in incomplete or misleading interpretations of the knowledge structure of the entire conversation.

Research studies (A. L. Siebert-Evenstone et al., 2017) argue that the use of window stanzas as a unit of analysis can lead to "fragmentation" of the discourse, making it difficult to capture the complex interrelationships between concepts that develop over the course of the conversation. Analyzing only a small window of conversation can obscure important patterns of interaction and collaboration that emerge over time. Given the nature of the activity, students playing Tic-tac-toe to elicit computational thinking, a shorter window stanza might loose important connections between concepts.

Instead, analyzing twenty lines of conversation allows for a more comprehensive understanding of the structure and dynamics of the knowledge network being constructed through the discourse interactions. By examining twenty lines of the conversation, it is possible to identify recurring themes, key ideas, and the relationships between different concepts, which can provide valuable insights into the knowledge-building process.

Why Use ENA?

The conventional method of coding and counting is widely used to provide a comprehensive qualitative analysis of verbal data. However, this approach may not fully capture the patterns and co-occurrences of the conversations between students. To overcome this limitation and gain a more nuanced understanding of the dynamics of these conversations, researchers have increasingly turned to the use of Epistemic Network Analysis (ENA). A different study (Csanadi et al., 2018) highlights that ENA can model patterns in the co-occurrence of socio-cognitive events, visualize these co-occurrences in the form of epistemic networks, and interpret how patterns differ from one another. In their study, the authors found that ENA revealed relationships that were not discovered through traditional coding-and-counting approaches, highlighting its potency as a tool for understanding how learners engage in activities and how that cognitive engagement contributes to learning. Overall, ENA represents a powerful and effective approach for analyzing verbal process data, providing researchers with valuable insights that would be challenging to obtain through other means.

Traditional coding helps us prepare the data to analyze, but to visualize the patterns and co-occurrences in the conversation between students, ENA provides plots with nodes and arches that help visualize the meaning of the conversations.

Human Subjects Considerations

This research study was conducted in collaboration with the university and a school district. The study was approved by two Institutional Review Boards (IRBs), one at the university and one at the school district. The research study was carefully reviewed and deemed ethical and safe to conduct under the C-SPECC grant (NSF 1736209).

Furthermore, before the study began, students and their parents were informed about the project and provided with details about what their participation would involve. This informed consent ensured that individuals who participated in the study understood the nature of the research, the potential risks, and benefits and had the opportunity to ask questions before agreeing to participate. The parents and students signed the consent form, indicating they understood the study and agreed to participate.

The principals, coordinators, and schoolteachers were also informed of the video recordings. The information was shared to ensure that all parties involved knew of the research and could provide support and assistance.

Population and Sample

Description

The data collection method used in this study involved observations in the classroom and the use of video recordings, which served as the primary source of data. The instrument used for data collection was a verbatim transcription, which allowed for the documentation of conversations during the solution of the Model Eliciting Activity in the Cybersecurity class.

Coding

The first stage after transcribing the video recordings was coding. Codes are used to retrieve and categorize similar data units to cluster segments related to the research question. I used pattern and simultaneous coding, according to the categories of computational thinking and characteristics of cognitive engagement. Pattern coding condenses large amounts of data into smaller number of categories or concepts (Lotto, 1986).

Table 2

Coding Patterns

COMPUTATIONAL THINKING CATEGORIES	COGNITIVE ENGAGEMENT CHARACTERISTICS
Decomposition	Self-regulation
Pattern recognition	Exchanging ideas
Abstraction	Giving directions
Algorithm	Justifying answers
	Asking questions
	Uptake

Table 2 shows the different codes used to classify the utterances of conversations, the purpose of this coding is to understand what categories and characteristics are more used by the teams. Conversations were double-coded (woman and man) and interrater reliability was calculated to assure validity of the data. Coders where I and Engineering Doctoral student that was trained and given bibliography on cognitive engagement and is knowledgeable in computational thinking. Social moderation was used to increase the value of interrater reliability.

Participant Selection

The teams, which included an all-women team, were part of a cybersecurity course in a South Texas high school classroom that consisted of 90% male students. They were tasked with solving the Tic-tac-toe MEA (Carmona et al., 2019), which required students to develop a set of rules to help a machine play Tic-tac-toe with a human and win every time. Discourse analysis and ENA (Epistemic Network Analysis) were used to identify differences and similarities between the participants' dialogues while working on the MEA. The participants jointly solved the MEA, considering their cognitive engagement and contributions to the solution as part of their Utility SVT (Subjective Value Task). During the coding of the transcriptions, coders had to identify if students where cognitively engaging, if they were a 1 code was added to the type of cognitive engagement and if there was no engagement then a 0 was added.

For the purpose of this study, we selected two different teams from a classroom of 37 students, only 3 women and the rest men. Their conversations were transcribed and analyzed. The teams consisted of the following:

1. All-women team.
2. All-men team.

Data Sources

Data were collected from two different sources, the observations I made in the classroom on the week prior to the completion of the Model-Eliciting Activity and the video recordings obtained on the day the classroom completed the MEA. I collected data in field notes to capture meaningful aspects of the context and situation of the classroom.

The conversations from our target teams were observed, audio, and video recorded. Video and audio recordings were transcribed verbatim. The data used for the study was segmented by utterance, that is one segment for each time someone spoke in a conversation. Afterwards, the conversations were double coded by a man and a woman coder and analyzed through the lens of discourse analysis. ENA was used to explore patterns and co-occurrences in the conversations. The class completed the MEA during one-class period.

ENA allows me to understand when and how each member of the team is making meaningful conversations and are eliciting the concepts by offsetting the quantity and focus on the quality of the conversations (Shaffer et al., 2016).

A subtracted cognitive network (Shaffer et al., 2016) was used to contrast those aspects of computational thinking and cognitive engagement in an activity more frequently used by the different teams; recognizing these differences can provide teachers and administrators with the necessary tools to promote equal participation of women in the Cybersecurity classroom. This analysis helped us understand similarities and differences on how a team of all women and a team of all-men cognitively engage in a Model Eliciting Activity that elicits computational thinking.

Data Collection

Researchers recorded the conversations of participants solving a Model Eliciting Activity (MEA) by using video cameras. The recordings captured the interactions among team members, which were later transcribed verbatim. Data was collected from the transcripts of the conversation between teammates as they were solving the MEA while eliciting computational thinking and engaging in different ways during the activity.

Transcription: The verbatim transcription of the video recordings was done by transcribing everything that is said in the conversation without altering the content or structure of the original interaction. This process captured all the verbal and non-verbal elements, such as pauses, intonation, and tone of voice, which can provide crucial information about the conversation's context. Transcripts with notes were added to understand the context and meaning of the conversations.

Instrumentation

The data was collected during one 45-minute class period in which the students worked on solving the Model Eliciting Activity. The students moved to the school library during their class period in order to complete the activity. The setting in the library allowed the students to sit together with their teams. Each team had three or four participants with the following composition (the number of participants in each group was dictated by the demographics of the classroom, limitation of the study):

- Category 1: Three women
- Category 2: Four men

Procedure

The students were given an open-ended task about artificial intelligence for high school students. A model-eliciting activity was designed to help students understand computational thinking while they understand basic concepts of machine learning (Carmona et al., 2019). The students were provided with either a short article or a video on machine learning and the Turing test. The article and video gave students an opportunity to situate the activity in a context that is meaningful for students and that provides the setting in which ideas and models of computational thinking emerge. After the students read the article or watched the video, they were split into groups of three and four students. Once in their group, they were asked to devise a set of rules and a procedure to help a machine play tic tac toe with a human and win every time. Each team had to play and understand the game and was asked to develop an algorithm that would make the machine win every time.

The students worked on solving their MEA for one class period that consists of 45 minutes of class. Each team was allowed to discuss the possible solutions and come up with what they considered the best solution to the problem. During the process of solving the MEA, the teammates elicited concepts of computational thinking and incorporated conversation about the four pillars I used for the operationalization of computational thinking: decomposition, pattern recognition, abstraction and algorithm creation. Each student cognitively engaged in different ways, either asking questions, giving directions, justifying answers, exchanging ideas, self-regulating or uptaking concepts, all characteristics of cognitive engagement (Gladstone et al., 2022).

A validity analysis process was used to evaluate if ENA accurately measured the conversations between students. To assess whether the data collected accurately represented the events and relationships studied, I used a combination of qualitative and quantitative methods. Qualitatively, I examined the data looking for patterns and themes the students used to describe how they solved the model-eliciting activity using the computational thinking categories and cognitive engagement characteristics. Quantitatively I calculated the inter-rater reliability, I used social moderation to discuss codes and achieve a higher Rho value. Interrater reliability quantifies the degree of agreement or consistency between two or more coders when assigning categorical or numerical codes to the same set of data. Cohen's Kappa assesses the extent of agreement between coders, accounting for the possibility of agreement occurring by chance, the measure yields values ranging from 0 to 1, where higher values indicate greater reliability. Inter-coder reliability involves having multiple coders independently analyze the same data and then comparing their results to ensure that they are consistent. This technique is commonly used in qualitative research to establish the trustworthiness and credibility of the data (Lotto, 1986).

In this study, two coders were trained to identify and code instances of computational thinking constructs and cognitive engagement constructs within the group conversations during the Model Eliciting Activity. I created a codebook with the definitions of each construct and the keywords to look for during the conversation. The coders independently analyzed a sample of the data and their results were compared to assess the level of agreement between them. This process was repeated until a high level of inter-coder reliability was achieved, indicating that the data was analyzed consistently and accurately.

Using inter-coder reliability is important for ensuring the reliability of data as it allows for multiple perspectives and reduces the potential for individual bias or error. By establishing an inter-coder reliability higher than 0.8, the data collected in this study can be considered consistent, providing a foundation for the research findings and conclusions.

Limitations

The number of women in the classroom was limited, I was only able to observe and video-record one group for each of the categories containing women as their participants. The number of men in the classroom was more than 30, I had to divide the men’s groups into groups of 4, the data obtained from the conversations the results of the ENA plots could be influenced by this matter.

Data Management

The dataset resulting from the transcriptions of team conversations was digitally stored on password-protected computers managed by the researcher and her advisor (Co-Principal Investigator of the C-SPECC grant). To ensure privacy, the identities of the students and teachers were replaced with pseudonyms. The names of the school and independent school district were also concealed to further safeguard the privacy of the individuals involved.

Data Analysis

Coding for computational thinking and cognitive engagement: To understand how participants engage in the activity and elicit computational Thinking, the researchers code the conversation for these constructs. The coding process involves identifying when each of the participants was talking about the constructs operationalized both for computational thinking and for cognitive engagement.

Data must be coded prior to using the Epistemic Network Analysis method. The team's conversation was coded into four different categories characterizing computational thinking using (Krauss & Prottsman, 2016) framework (Table 2). Engagement in the activity was coded using the different categories of cognitive engagement (Gladstone et al., 2022) (Table 3).

ENA allowed us to identify which characteristics of computational thinking and their connections to each participant's utility SVT were elicited during the process of solving the MEA. When the researcher runs the ENA web tool, the algorithm adds the co-occurrences in the conversations of each group that is being analyzed. After running the program, ENA gives us plots and graphs with the information obtained from the coded information. Each time the students mention one of the codes, in this case computational thinking, or cognitively engages in a certain way, ENA adds a co-occurrence. When the researcher defines the window stanza, she is indicating how many lines of conversation will the tool analyze to see how many connections between codes are being made. The connections then form the lines between each code. After doing the computation, the tool provides us with a graph with nodes that connects with arcs, these nodes and arcs have different size and width. The larger nodes indicate that code has been mentioned more times, the thicker lines indicate that that pair of codes has been connected more times, this means, more times during the conversation the students related two different codes.

Finding ENA's subtracted networks allowed to compare between team members. ENA also allowed to identify if the participants in the teams were engaged in the activity and how they engaged. ENA allows us to understand when and how each member of the team is making meaningful conversations and are eliciting the concepts by offsetting the quantity and focus on the quality of the conversations (Shaffer et al., 2016).

Data interpretation: To analyze the coded data, I used Epistemic Network Analysis. Researchers interpret the coded data to identify patterns and themes that emerge from the conversation. The interpretation provides insights into the participants' cognitive engagement and their computational thinking practices.

Codebook

I will provide three tables with the definitions that the coders used to identify the different codes in the conversations during the completion of the Model-Eliciting activity. Table 3 are the computational thinking categories, Table 4 the cognitive engagement characteristics.

Table 3

Computational Thinking Constructs

Name	Definition
Decomposition	Identify when the students are talking about part of the problem and how to solve it, when they break down the problem into smaller parts that are easier to manage.
Pattern Recognition	When the students start to identify repetitions and similarities in the problem. The students can detect patterns when they are comparing instructions.
Abstraction	Once the students understood the problem they are solving and they have identified patterns, the students are able to generalize the solution. Abstraction will be identified when students are able to come up with solutions that work for every time they are presented with the problem.
Algorithms	Students come up with a set of steps to follow to obtain their optimal solution.

Table 4

Cognitive Engagement within SEVT Constructs

CODE	DESCRIPTION
Self-Regulation	Self-regulation, according to Eccles and Wigfield (2002), refers to the process through which individuals actively monitor and control their thoughts, feelings, and behaviors in order to achieve their goals. This includes setting goals, planning and organizing one's time and resources, monitoring progress, and adapting strategies as needed. Self-regulation also involves the ability to regulate one's emotions and motivation, to persist in the face of obstacles and setbacks, and to self-evaluate one's progress towards achieving the goal. Overall, self-regulation is seen as a critical component of achievement motivation, as it allows individuals to direct their efforts towards meaningful goals and to adjust their behavior as needed in order to achieve those goals.
Exchanging ideas	Process of sharing and discussing ideas, perspectives, and insights with others. More specifically, exchanging ideas involves the communication of thoughts and concepts among individuals or groups with the goal of building mutual understanding, increasing knowledge, and generating new insights. This exchange can take many forms, including discussions, debates, brainstorming sessions, and collaborative problem-solving activities. In the context of motivation and learning, exchanging ideas can be particularly valuable as it can help individuals to clarify their own beliefs and goals, challenge and refine their understanding, and learn from the experiences and perspectives of others. Through this process, individuals can gain a deeper appreciation of the complexity of the learning process and develop new strategies and approaches to enhance their motivation and performance.

Table 4 (Continued)

Giving directions	Providing guidance or instructions to individuals in order to help them achieve their goals. More specifically, giving directions involves communicating specific steps, strategies, or actions that individuals can take to move towards their desired outcome. These directions can be provided in a variety of formats, such as verbal instructions, written guidelines, or visual aids. In the context of motivation and learning, giving directions can be an important part of helping individuals to understand what is expected of them and how they can best achieve their goals. Clear and concise directions can provide individuals with a sense of structure and direction and help them to feel more confident and competent in their abilities. However, it is important to note that giving directions is just one part of the motivation and learning process, and that individuals also need to be able to set their own goals, make choices, and take ownership of their learning in order to be truly motivated and successful.
Justifying answers	Process of providing evidence or reasons to support a particular response or solution to a problem. More specifically, justifying answers involves explaining why a particular response or solution is valid or appropriate, using logical reasoning and relevant evidence. This process of justification requires individuals to think critically and reflect on their own thinking, as well as consider alternative perspectives or solutions. In the context of motivation and learning, justifying answers is an important skill for individuals to develop as it can help them to understand and articulate their own thought processes, evaluate the quality of their own and others' reasoning, and engage in productive discussion and debate. By justifying their answers, individuals can also develop a deeper understanding of the concepts and ideas they are learning, and become more confident in their ability to apply these concepts in new and unfamiliar situations. Overall, justifying answers is an important part of the learning process as it promotes critical thinking, reflection, and the development of deeper understanding and knowledge.
Asking questions	Process of seeking information, clarifying understanding, and exploring ideas through inquiry. More specifically, asking questions involves actively seeking out information, insights, and perspectives through inquiry, either by posing questions to oneself or to others. This process of questioning requires individuals to engage in critical thinking and reflection, as well as demonstrate curiosity and a willingness to learn. In the context of motivation and learning, asking questions is an important skill for individuals to develop as it can help them to clarify their understanding, identify gaps in their knowledge, and generate new insights and ideas. By asking questions, individuals can also deepen their cognitive engagement with the material they are learning and develop a more nuanced and sophisticated understanding of complex concepts. Moreover, asking questions can also foster a more collaborative and interactive learning environment, where individuals can engage in discussion and debate, share their ideas and perspectives, and build on each other's knowledge and understanding. Overall, asking questions is an essential part of the learning process, as it promotes curiosity, critical thinking, and the development of deeper understanding and knowledge.

Table 4 (continued)

Uptake	Process of taking in or internalizing new information, ideas, or skills. More specifically, uptake involves actively engaging with new information or ideas, making connections between new and existing knowledge, and integrating new insights or skills into one's existing mental framework. This process of uptake requires individuals to actively process and synthesize new information, as well as engage in self-reflection and self-evaluation to assess their own understanding and progress. In the context of motivation and learning, uptake is an important component of the learning process as it allows individuals to build upon their existing knowledge and develop new skills and competencies. Effective uptake involves not only acquiring new knowledge or skills, but also making meaningful connections between different pieces of information and applying new insights or skills in real-world contexts. Moreover, effective uptake is often linked to intrinsic motivation, as individuals who are highly motivated to learn are more likely to actively engage with new information and ideas and take ownership of their own learning process. Overall, uptake is an essential part of the learning process, as it promotes deep understanding, skill development, and the ability to apply new knowledge in meaningful ways.

CHAPTER FOUR: FINDINGS

Introduction

The purpose of this study was to examine high school women's and men's cognitive engagement in a Model Eliciting Activity (MEA) that elicits computational thinking, analyzing the relationship between cognitive engagement and computational thinking for women and men, and finding similarities and distinctions between the two groups (all-women and all-men). The analysis was focused on terms of the two research questions:

- **RQ1**. How does students' cognitive engagement relate to computational thinking while they are solving the Tic-tac-toe MEA?
- **RQ2**. What are similarities and distinctions between the two teams, depending on team members' gender (one all-women team and one all-men team)?

The study unfolded through various phases. I began with a qualitative approach, observing the classroom, capturing video recordings of two teams' discussions while solving the activity, transcribing, coding, and analyzing the conversational exchanges among the participants of each team. I followed with discourse analysis and coding of the different categories of computational thinking and characteristics of cognitive engagement. Then, employed a network approach, using Epistemic Network Analysis (ENA). This technique allowed me to identify co-occurrences in the dialogues that highlighted the computational thinking and cognitive engagement constructs as both teams solved the Tic-tac-toe MEA. I wanted to see whether each team's approach was uniquely different; analyzing on how the women's team tackled the task to promote participation of women in STEM.

Qualitative Data Analysis

Participants

One team was composed by three women and the other one had four men. Both teams were part of the same cybersecurity course in a South Texas high school classroom that consisted of 90% male students.

The team comprised solely of women had three participants, generating a total of 112 conversation lines or utterances. Each utterance reflected a distinct idea or sentence that the students articulated. On the other hand, the all-men team, consisting of four participants, produced a significantly larger total of 370 lines of conversation. The number of lines held in the man's conversation was larger because of the extra participant on the team and because of several off-topic conversations the men had.

Epistemic Network Analysis was used to identify differences and similarities between the participants' dialogues while working on the MEA. Each team of participants jointly solved the MEA, considering their cognitive engagement and contributions to the solution as part of their Utility SVT (Subjective Value Task).

Coding

Following data collection and transcription, the conversation lines were coded in accordance with the four codes for computational thinking and the six codes for cognitive engagement constructs.

The conversations were double coded employing Krauss and Portman's (2016) computational thinking taxonomy, coupled with Gladstone's (2022) cognitive engagement constructs, which are rooted in Eccles and Wigfield's (2020) Situated Expectancy Value Theory.

Table one illustrates each construct's name, the definition utilized in the codebook, and an example for each one of the teams.

The conversations were double coded by a woman and a man coder. The measure for data analysis was the co-occurrences of constructs for computational thinking and engagement in the conversations. ENA was used to explore patterns and co-occurrences in the conversations.

Table 5

Computational Thinking Constructs with Examples

NAME OF CATEGORY	DEFINITION	EXAMPLE WOMENS	EXAMPLE MENS
Decomposition – Computational Thinking	Breaking down problem into smaller more manageable parts.	So, we have to come up with like different, I guess scenarios of how it can play out	you're first set up the strategy
Pattern recognition	Identify repetitions and similarities in the problem.	So basically… if the computer starts first, it would start in a corner, right?	If someone is to place in the middle as their second term is the result drawn every time.
Abstraction	Generalize the solution, solutions for every time they are presented with the problem.	Because if you go second you can always guarantee a draw	Second per second gonna be harder to make that the center space
Algorithms	Set of steps to follow to obtain optimal solution.	So we can put: if computer goes first put/place "x" in a corner space, if computer goes second, if center is not taken, take center	player two goes second and then alternate until a draw

Table 6

Engagement in SEVT with Examples from Data

NAME OF CHARACTERISTIC	DEFINITION	EXAMPLE WOMENS	EXAMPLE MENS
Self- regulation	Actively monitor and control their thoughts. Direct efforts towards meaningful goals.	(Algorithm does not work) We are not the computers…	I just want to follow one step at a time
Exchanging ideas	Sharing and discussing ideas, perspectives and insights with others.	So that is why you never put it in like one of those spaces	its set. This are the same set. These are the same steps

Table 7 (continued)

Giving Directions	Providing guidance or instructions to individuals to help them achieve their goals. Communicating specific steps.	I go here, you go here	so you have to do that, so its the robot's turn
Justifying answers	Providing evidence or reasons to support a particular response. Explaining a particular response.	Were the computer never loses a game, regardless if it starts, you see I think draws are… can we do draws?	so now they can do whatever they want but the most popular
Asking questions	Seeking information, clarifying understanding and exploring ideas through inquiry.	Were the computer never loses a game, regardless if it starts, you see I think draws are… can we do draws?	then what is the scenario?
Uptake	Taking in or internalizing new information, ideas or skills. Actively engaging.	Bigger groups for this would have been nice (inaudible)	NA

Table 5, and 6 provide us an example of the lines of conversations had by the women's team and the men's team during the activity.

Interrater Reliability

The double-coded conversations (by a woman and man coders) followed a process of social moderation to reach an agreement on the final coding (Frederiksen et al., 1998). The process of coding was carried out in two stages. First stage the coders coded for the four computational thinking constructs and the six cognitive engagement constructs. The coders added comments in the utterances that were different to include in the social moderation. After social moderation, all the constructs reached Kappa higher than 0.80. Interrater reliability, often measured by Cohen's Kappa coefficient, refers to the consistency of the evaluation scores given by multiple raters. A high Kappa score, such as 0.8 or above, indicates significant agreement among raters beyond mere chance, which in turn boosts the credibility of the research findings. It is critical to strive for a high Kappa value as it ensures that the measurement tool is consistent and reliable, suggesting that it would likely yield similar results if applied again under the same conditions. However, the acceptable level of Kappa can vary depending on the specific context and objectives of the study.

Epistemic Network Analysis

To determine how student cognitive engagement relates to computational thinking while solving the Tic-Tac-Toe MEA, we separately analyzed the conversation between the three women and the four men in their respective teams and plotted an epistemic network for each team.

In the analysis of the conversations, I examined a window stanza comprising 20 utterances. In this study, opting to analyze a window stanza of 20 lines or utterances was deemed more favorable than restricting the examination to a smaller window stanza of merely four lines of conversation (ENA's webtool default). This preference arises from the recognition that the meaning of individual statements may be significantly shaped by the context within which they are situated. Consequently, the analysis of only a small window of conversation could yield incomplete or misleading interpretations of the knowledge structure embedded within the entirety of the conversation.

To streamline the complexity of the Epistemic Network Analysis (ENA) graph, I employed mean rotation (MR1) to align the centroids of the two tasks on the x-axis. Meanwhile, I used singular value decomposition (SVD2) on the y-axis. Here, the x-axis signifies the dimension that accounts for the largest portion of explained variance, while the y-axis represents a dimension orthogonal to the first dimension, as per the methodology outlined by Wooldridge et al. (2019).

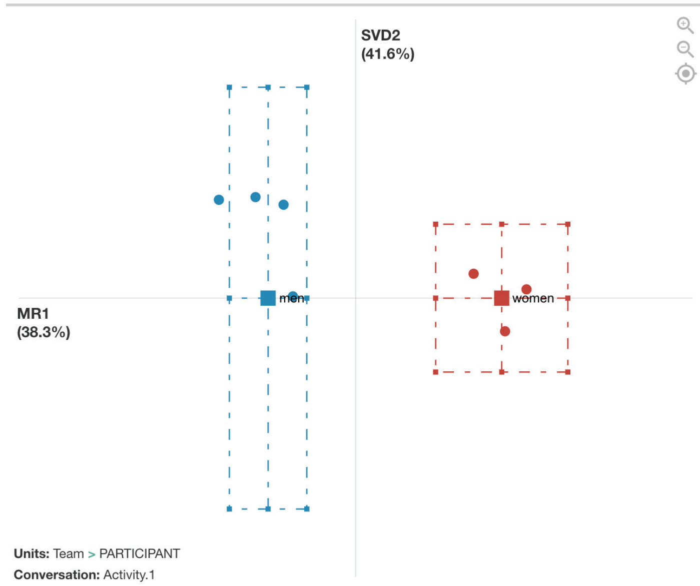

Figure 3

Confidence Intervals, MR1 and SVD

Figure 3 shows the confidence intervals for the two groups (women and men). The confidence intervals show that there is a statistically significant difference between the teams, this gives me a green light to continue the analysis and try to answer the research questions.

To answer research question 1: how does student cognitive engagement relate to computational thinking while solving the Tic-tac-toe MEA? We plotted the conversations held in each of the teams.

Figure 4

Women's Conversation Network

In Figure 4, we observe that the women develop notions of computational thinking (CT), mainly through decomposition, as we can see with the largest node, followed by abstraction, pattern recognition and algorithms. Moreover, while they are developing these CT notions, they are cognitively engaged through a broad variety of strategies: mainly, asking questions, justifying answers, exchanging ideas, and self-regulating. The strongest connections are between decomposition (CT) and asking questions, justifying answers, exchanging ideas and self-regulating.

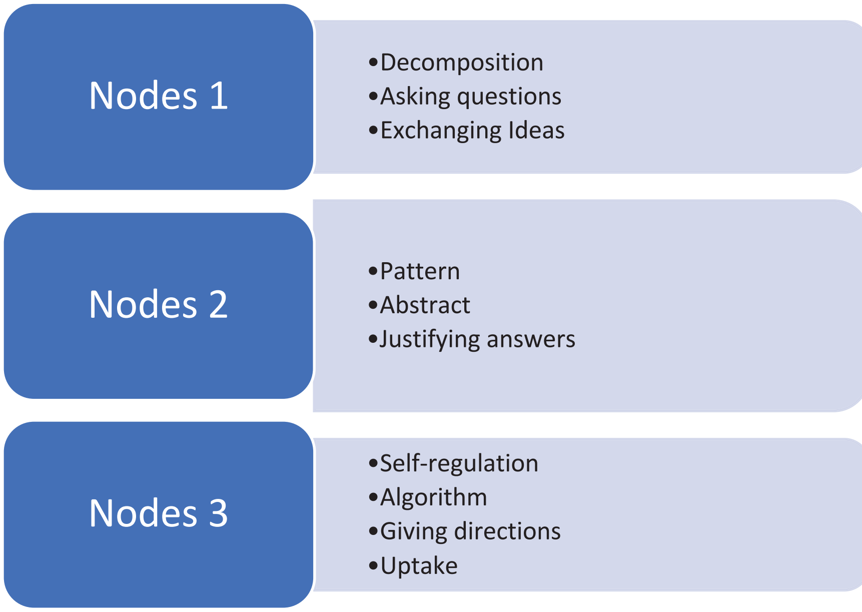

Figure 5

Women's Co-occurrences – Nodes

Figure 5 represents three different groups of constructs mentioned during the conversations, they are ordered by size of node, first two groups are the three largest (codes with highest co-occurrences), second group corresponds to the three codes with less co-occurrences than the high intensity of co-occurrence group, and the third group are the nodes that where least mentioned during the completion of the MEA. Nodes 1: The women's team mentioned decomposition and asked questions and exchanged ideas at the highest rate. Nodes 2: They talked about patterns, abstracts and justified their answers with a lower rate than the first group before but with significant mentions. Nodes 3: They had few instances where they self-regulated, talked about algorithms, gave directions or had uptakes.

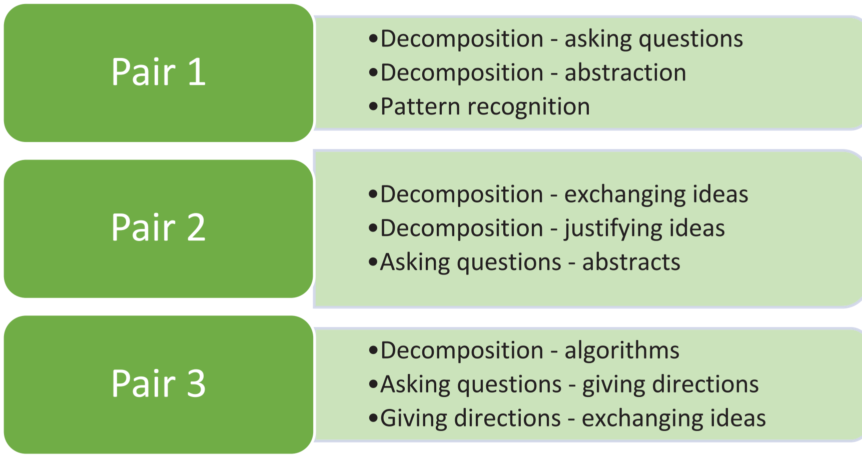

Figure 6

Women's Conversation Pairs

To give an easier visualization on the results of the ENA plots, I divided the pairs of conversation coded in three categories, the first one is the group with the three pairs with the highest connections, the second one is with the ones that had considerable amount of connections but where visibly smaller than the first category (second three) and the last one has the three pairs that had the least connections. Only three pairs of conversation were selected for each group, all the other connections between nodes had smaller co-occurrences. Figure 6 represents the 3 groups of pairs with more conversations between categories and characteristics of computational thinking and cognitive engagement, in the first group with the highest co-occurrences of conversations between constructs. These plots and figures help us answer the research question, the students in the women's team are developing the constructs in computational thinking (Carmona & Galarza, 2021) and they are cognitively engaged through different engagement strategies, mainly asking questions, and justifying their answers.

Figure 7

Men's Conversation Network

The way in which the all-men team developed computational thinking was different than the all-women team's solution process. In Figure 7, we observe that the all-men team's notions of computational thinking were organized through interactions between abstraction with cognitive engagement categories and with pattern recognition codes, and they rarely utilized decomposition. While they developed these notions of CT, they were also cognitively engaged using a variety of the six strategies, which all seem to be connected more strongly with abstraction, then patterns, and then algorithms. A powerful strategy for this team to abstract and find patterns was to justify answers, exchange ideas, and give directions. The strongest connections are between computational thinking codes was between abstract and patterns (CT), on the other side, they connected exchanging ideas and giving directions.

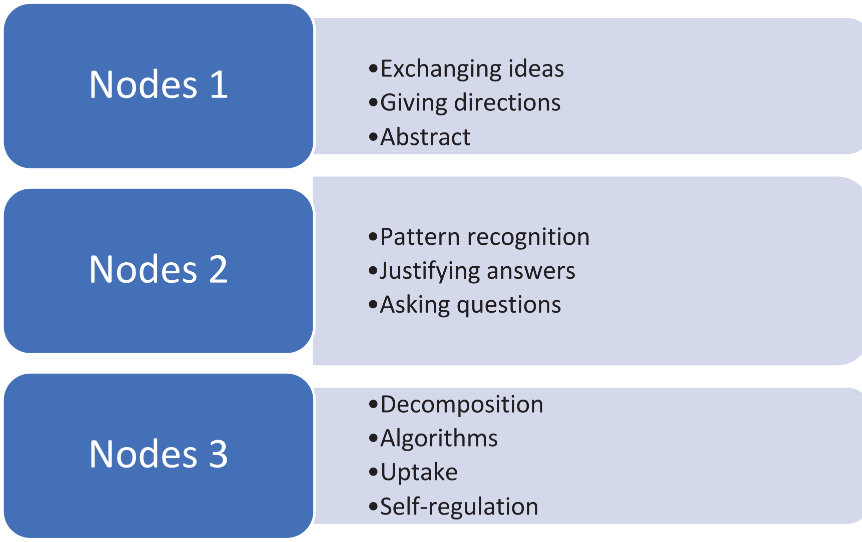

Figure 8

Men's Co-occurrences – Nodes

The same classification of groups for visualization apply for the men's team. Figure 8 represents three different groups of constructs mentioned during the conversations, they are ordered by size of node, first two groups are the three largest (codes with highest co-occurrences), second group corresponds to the three codes with less co-occurrences than the high intensity of co-occurrence group, and the third group are the nodes that where least mentioned during the completion of the MEA. Nodes 1: The men's team exchanged ideas, gave directions and abstracted at the highest rate. Nodes 2: They talked about patterns, justified their answers, and asked questions with a lower rate than the first group before but with significant mentions. Nodes 3: They had few instances where they decomposed, talked about algorithms, had uptakes and, self-regulated.

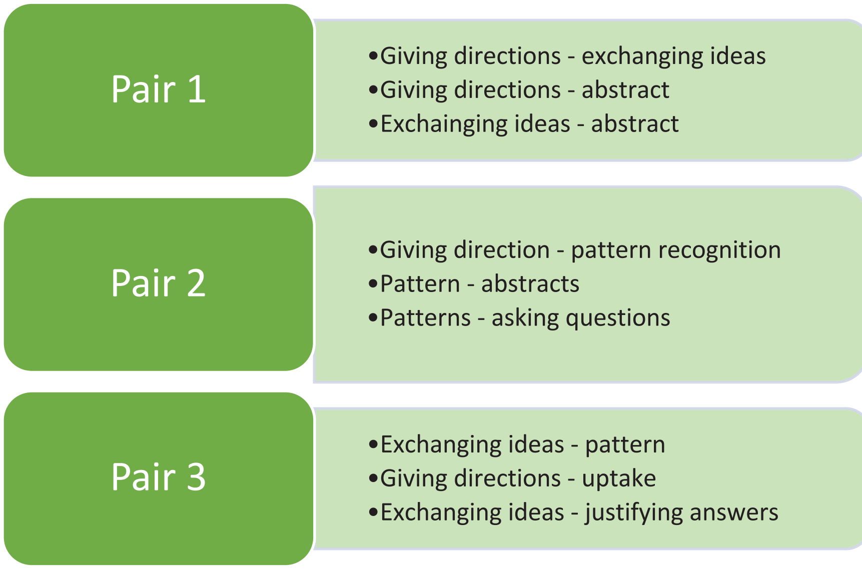

Figure 9

Men's Conversation Pairs

Classification of groups of pairs is same as the women's team. Figure 9 represents the 3 groups of pairs with more conversations between constructs in the all-men team. In the first group: exchanging ideas-giving directions, exchanging ideas-abstract, and giving directions-abstract. In the second group they talk about giving directions-patterns, abstract-patterns, patterns-asking questions. The third group has manly interactions between exchanging ideas-patterns, giving directions-uptake, exchanging ideas-justifying answers. These plots and figures help me answer the research question, both women and men cognitively engage in the Model Eliciting Activity while they elicit the different categories of computational thinking. The plots show there is a distinct way of cognitively engaging and eliciting computational thinking for women and men.

If we compare the figures between the all-women and the all-men teams, we are able to start answering the second research question, the similarities and distinctions between the teams, depending on their gender composition. As can be observed in the figures and in the plots, both teams elicit computational thinking, they both are cognitively engaged while eliciting CT, but the way they do it is different. For the women's team, decomposition and asking questions are the most repeated codes and for the men's team, they are giving directions, exchanging ideas, recognizing patterns and abstracting more often.

To further understand the differences, I plotted a subtracted network to mark the differences in co-occurrences between both teams.

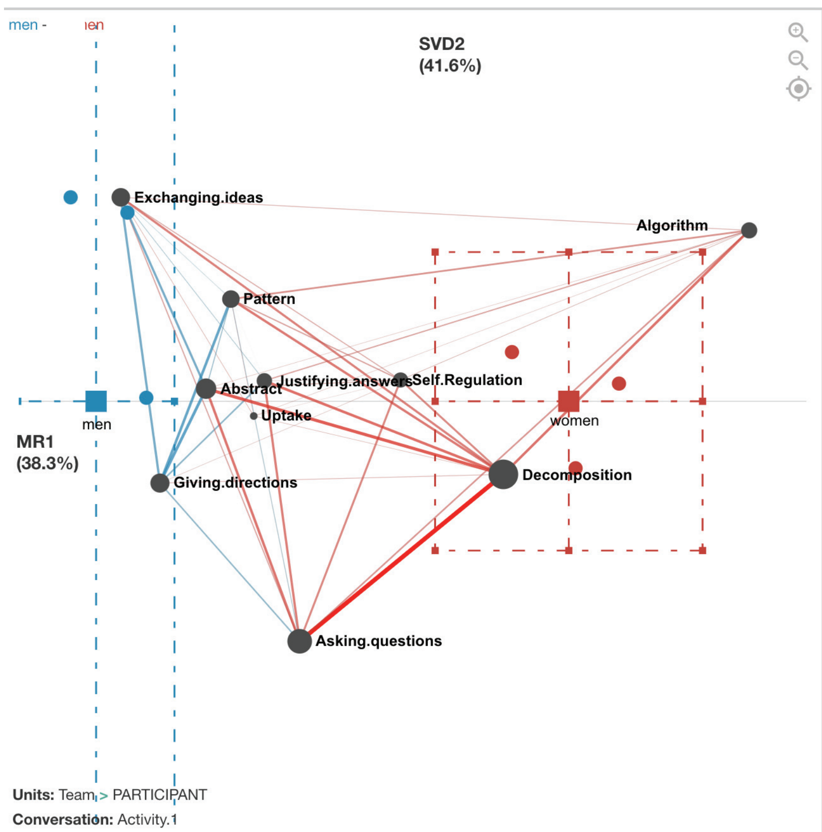

Figure 10

Subtracted Networks Between All-men and All-women Teams

Figure 10 is the subtracted network that shows us the differences in co-occurrences between the all-men's and the all-women's teams. These are marked by wider lines between the codes which indicate that one team had more connections between those pairs than the other team. With the subtracted ENA plot we note that for computational thinking, the all-women's team had greater co-occurrences of abstract-decomposition, algorithm – decomposition, and pattern-decomposition; whereas the all-men's team had greater co-occurrences between abstract-pattern. This indicates that when the all-women's team elicited computational thinking, they went from abstraction to/from patterns by breaking the problem into smaller pieces (decomposition). Instead, the all-men's team went directly from patterns to/from abstract without mediation. In terms of cognitive engagement, the all-women's team showed a greater and more varied set of co-occurrences amongst characteristics for cognitive engagement. Interestingly for the women, all six characteristics for cognitive engagement were connected to decomposition (computational thinking). This shows that the team of women was highly engaged cognitively in developing notions of computational thinking. For the men's team, the greater co-occurrence between cognitive engagement and computational thinking was between abstraction and giving directions and justifying answers. This evidence the relevance of argumentation in the men's development of abstraction in computational thinking. In summary, the women's team showed many ways in which they cognitively engaged in developing computational thinking. Whereas the men were cognitively engaged mainly through justification and argumentation.

In summary, we observe that both teams were cognitively engaged in the problem-solving episode by noting the large number of co-occurrences amongst all six characteristics for cognitive engagement. However, we also observe that each team elicits computational thinking in different ways, with women developing decomposition, abstraction, and patterns; whilst the men developed abstraction and patterns with little mediation from decomposition.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

Introduction

In this chapter I summarize the study and the conclusions drawn from the analyzed data from the previous chapters. It engages in a discussion concerning the implications specific to the discipline and extends to the broader professional implications. The chapter culminates with suggestions for subsequent research.

Summary of the Study

Overview of the Problem

This study responds to the underrepresentation of women in STEM fields. Despite efforts to improve gender equity, women still only constitute a small percentage of the STEM workforce. This shortage threatens economic and national security interests. Research indicates that providing high-quality, cognitively engaging STEM learning opportunities for women early on can increase their motivation and success in these fields. However, barriers persist that limit women’s access, participation, and sense of empowerment in STEM.

For example, studies show women tend to have lower self-efficacy and interest in STEM than men, partly due to negative stereotypes about their abilities. Biases in classroom environments and curricula can also discourage women from fully engaging in STEM learning. These barriers accumulate over time, leading fewer women to pursue advanced STEM education and careers. Consequently, women comprise only 28% of STEM workers despite representing 50% of the overall workforce.

This study aims to examine women’s cognitive engagement in STEM activities, specifically for computational thinking elicited through model-eliciting activities (MEAs), to uncover strategies for promoting women in STEM. Understanding how women cognitively interact with STEM learning environments can provide insights into creating more motivating, empowering experiences. Analyzing their computational thinking processes can also reveal skills educators should target to increase women's' persistence and success in STEM fields. Ultimately, this research strives to identify evidence-based approaches for cognitively engaging women in STEM and opening pathways for their advancement.

Purpose Statement

This study proposes to examine women's and men's engagement in a Model Eliciting Activity (MEA) that elicits computational thinking, analyzing the relationship between cognitive engagement and CT for women and men. Focusing on how women cognitively engage in STEM, as described by the Situated Expectancy Value Theory, this study seeks to explore potential differences between men and women in eliciting computational thinking. The primary objective of this study is to enhance our understanding of women's engagement in STEM activities, with a specific focus on MEAs that elicit computational thinking, and to investigate whether there are gender differences in the ways in which men and women elicit computational thinking.

The study's primary objective is to enhance our understanding of women's cognitive engagement in STEM-related activities, using an MEA to elicit computational thinking. It also aims to identify any potential differences in the strategies employed by men and women to elicit computational thinking.

Research Questions

- **RQ1.** How does student cognitive engagement relate to computational thinking while solving the Tic-tac-toe MEA?
- **RQ2**. What are similarities and distinctions between the two teams, depending on team members' gender (one all-women team and one all-men team)?

Review of the Methodology

Epistemic network analysis (ENA), a quantitative ethnographic technique, was then used to model the relationships between codes based on their co-occurrences within the discourse. ENA network visualizations were used to represent the interconnections and relationships between computational thinking and cognitive engagement constructs within each team's discussions. The examination of the conversations of an all-women team and an all-men team as they collaborated to solve the Tic-tac-toe MEA. Their exchanges were coded for computational thinking and cognitive engagement constructs rooted in theory.

Subtracted ENA networks were also produced to compare the two teams' networks. This technique quantitatively highlighted differences in code co-occurrence patterns between the teams. Larger node sizes and thicker connecting lines indicated greater prevalence of certain codes and relationships for one team versus the other.

This methodology provided rich insights into how the two teams cognitively engaged and how they processed information, problem-solved collaboratively, and constructed knowledge representations to complete the task. The discourse analysis yielded an in-depth understanding of conversation dynamics while ENA offered a holistic visualization of conceptual connections revealing subtleties about the gendered groups' learning processes.

Overview of Participants, Data Collection, and Analysis

The participants were high school students from a cybersecurity class conformed mostly of male students. Two teams were observed: one all-women team (3 participants) and one all-men team (4 participants). Their naturalistic conversations while collaboratively solving the Tic-tac-toe MEA were video recorded, and then transcribed for analysis.

The transcripts were segmented into utterances representing distinct conversational turns. Each utterance was double coded by two independent coders for computational thinking skills (decomposition, pattern recognition, abstraction, algorithms) and indicators of cognitive engagement (self-regulation, exchanging ideas, giving directions, justifying answers, asking questions, uptake).

Epistemic network analysis (ENA) was then used to model the relationships between codes based on their co-occurrence within 20-line stanzas of conversation. ENA produced network visualizations with nodes representing the codes and connecting lines indicating relationships between them. Subtracted ENA networks were generated to highlight differences between the two teams' knowledge structures.

Major Findings

Key findings showed both teams elicited computational thinking and were cognitively engaged but in different ways. The women tended to progress from abstraction to decomposition when eliciting computational thinking, while the men directly connected abstraction and pattern recognition.

The women also demonstrated more varied cognitive engagement strategies tightly linked to computational thinking categories, especially decomposition. Their cognitive engagement was characterized by high levels of questioning, justification, and exchange of ideas around breaking down the problem.

In contrast, the men relied more heavily on justifying answers and giving directions related to abstracting patterns and algorithms. While engaged differently, both teams succeeded in developing computational thinking models to solve the Tic-tac-toe MEA.

These results suggest tailored strategies, such as MEAs, may be needed to optimize women's and men's unique cognitive engagement styles when fostering computational thinking.

Model-eliciting activities show promise for facilitating productive collaborative, cognitively engaging in computational thinking learning for both, women and men.

Unexpected Findings

An unexpected finding surfaced right from the onset, rooted in the demographic composition of the group. Within a high school located in South Texas, out of a cohort of 37 students, a mere 3 were women. This stark disparity in gender distribution not only reinforced existing data but also underscored the challenges associated with achieving gender equity in specific academic domains in certain regions. The observation served as a poignant reminder of the broader socio-cultural factors at play and the importance of fostering more inclusive educational environments.

Findings Related to the Literature

I previously presented the problem statement, underscoring the need to promote gender equity and women's representation in STEM fields (Bagchi-Sen et al., 2010). This study's findings provide empirical insights into differences in how high school women and men cognitively engage with computational thinking concepts elicited through model-eliciting activities. Research studies tell us how Model Eliciting Activities promote equity in participation and cognitive engagement of both men and women. The results of this research study can lead us to conclude that when we teach with a well-designed MEA, students will elicit computational thinking and cognitively engage in the activity. These results lead to a higher expectancy of success and motivation which could potentially provide students with an increased likelihood of continuing in the STEM path, helping solve the problem of underrepresentation of women in STEM and decrease the gap between jobs and professionals (Eccles & Wigfield, 2020a; Lesh & Doerr, 2003; Zawojewski & Carmona, 2001).

Specifically, the results reveal nuanced variations in the women's and men's collaborative exchanges and co-occurrence relationships between computational thinking categories and indicators of cognitive engagement. As the literature review in Chapter 2 suggested, tailored strategies may be required to optimize the unique learning processes of women and men in STEM education (Eccles & Wigfield, 2020; Lesh & Doerr, 2003).

The conceptual framework outlined in Chapter 2 integrates computational thinking, cognitive engagement rooted in situated expectancy-value theory, and model-eliciting activities as key elements of the research design and data analysis for this study. The results validate that these components can be systematically identified and modeled through discourse analysis and epistemic network analysis of students' conversational exchanges (Shaffer et al., 2009).

For instance, the women demonstrated extensive evidence of cognitively engaging in computational thinking practices like decomposition through strategies such as self-regulation, justification, and questioning (Appleton et al., 2006). In contrast, the men relied more heavily on justifying answers and giving directions associated with abstraction and pattern recognition, with fewer instances of varied cognitive engagement strategies (Greene, 2015).

Moreover, the results reflect constructs of cognitive engagement grounded in expectancy-value motivation theories highlighted in Chapter 2 (Eccles & Wigfield, 2020). Analyzing the co-occurrence of these engagement indicators provides insights called for by researchers into gendered motivational processes in STEM learning contexts (Eccles & Wang, 2016).

Overall, the discourse analysis and ENA networks generated evidence that women's and men's differential expression of computational thinking abilities and collaborative engagement styles present a logical continuation of the theoretical groundwork and rationale established in the first chapters. These results empirically extend key elements of the conceptual framework and literature review, providing data-driven insights into promoting gender equity in STEM engagement and education.

Conclusions

The study answers the research questions in the following manner:

RQ1. How does student cognitive engagement relate to computational thinking while solving the Tic-tac-toe MEA? We observe that both teams were cognitively engaged in the problem-solving episode by noting the large number of co-occurrences amongst all six characteristics for cognitive engagement.

RQ2. What are similarities and distinctions between the two teams, depending on team members' gender (one all-women team and one all-men team)? We also observe that each team elicits computational thinking in different ways, with women developing decomposition, abstraction, and patterns; whilst the men developed abstraction and patterns with little mediation from decomposition.

This study set out to examine women's and men's cognitive engagement in computational thinking practices elicited through a model-eliciting activity. The aim was to uncover potential gender differences that could inform strategies for bolstering women's representation and success in STEM fields.

The discourse analysis methodology allowed for an in-depth, contextualized analysis of two teams' conversational exchanges as they collaboratively solved the problem. Meanwhile, epistemic network analysis provided a holistic visualization of the connections between computational thinking skills and cognitive engagement constructs within the discourse.

Model-Eliciting Activities (MEAs) play a pivotal role in creating equitable learning landscapes that champion the cognitive engagement of students, irrespective of gender. In this context, both the all-women and all-men groups demonstrated successful cognitive immersion. Each student showcased the capability to excel and become deeply engaged with the task, primarily driven by its utility task value; in essence, they displayed a marked preference for the Tic-tac-toe activity over others. Given these findings, MEAs emerge as instrumental tools in promoting the cognitive engagement of women in STEM, ensuring their active participation while simultaneously ensuring that men remain inclusively engaged. This underlines the potential of MEAs in fostering an equitable STEM environment where every student can thrive.

These results highlight the need for nuanced approaches that align with the unique ways women and men engage with and process STEM concepts and problems. Educators must leverage pedagogical tools like model-eliciting activities that create supportive environments facilitating collaborative, cognitively engaging learning for diverse learners.

Ultimately, this research provides a model for digging deeper into gendered dynamics in STEM education and charting an equitable path forward where all students, especially historically underrepresented women, feel motivated, empowered, and set up for success in pursuing STEM disciplines and careers.

Recommendations for Further Research

Dynamics of Mixed Groups

Given the observed dynamics in gender-segregated groups, it would be enlightening to examine the dynamics of mixed-gender groups. This could offer insights into collaborative patterns, leadership roles, and the balance of contributions in diverse group settings.

Intersectionality of Participants

Beyond the focus on gender, it's vital to delve into the intersectionality of participants, studying how multiple social categorizations (e.g., race, class, and gender) intersect at an individual level, potentially creating overlapping systems of discrimination or privilege in STEM educational settings. This would require analyzing a greater number of student teams and contexts to allow for further generalizations.

Computational Thinking and Future Success

With computational thinking being a cornerstone in our education systems, there's a need to study how proficiency in this area correlates with future success in higher technological careers or baccalaureate paths. Investigating this could solidify the importance of computational thinking in early education and its direct implications on future career trajectories in STEM fields. These research directions would not only broaden the understanding of gender dynamics and equity in STEM but also provide educators and policymakers with actionable insights to create more inclusive and conducive learning environments.

APPENDIX

EXCERPT TRANSCRIPT OF TEAMS, CODED.

Clip Num	Activity	Team	PARTICIPANT	Activity	DIALOGUE	Self Regulation	Exchanging ideas	Giving directions	Justifying answers	Asking questions	Uptake	Decomposition	Pattern	Abstract	Algorithm
1	P7	women	S1 - girl	Tic-Tac-	Is there a way…. Is there a trick to tic-tac-toe? … is there a way to physically win every single time?	0	0	0	0	1	0	1	0	1	0
1	P7	women	S2 - girl	Tic-Tac-	No… if someone where to **(inaudible)** it's a **(inaudible)** draw… which isn't losing…cause it never says it can't be a draw, it says it doesn't loses	0	0	0	1	0	0	1	0	1	0
1	P7	women	S1 - girl	Tic-Tac-	It makes sense to me	1	0	0	0	0	0	0	0	0	0
1	P7	women	S2 - girl	Tic-Tac-	Cause you know that one trick, if you… I can't… lets see, if there's… I think it's the corner pieces	0	1	0	0	0	0	1	0	1	0
1	P7	women	S3 - girl	Tic-Tac-	…so are we writing methods or stuff like that?	0	0	0	0	1	0	1	0	0	0
1	P7	women	S2 - girl	Tic-Tac-	mmhh?	0	0	0	0	1	0	0	0	0	0
1	P7	women	S3 - girl	Tic-Tac-	We are doing methods?	0	0	0	0	1	0	1	0	0	0
1	P7	women	S1 - girl	Tic-Tac-	So we have to come up with like different, I guess scenarios of how it can play out	0	1	0	0	0	0	1	0	0	0
1	P7	women	S3 - girl	Tic-Tac-	Oh… ok	0	0	0	0	0	0	0	0	0	0
1	P7	women	S1 - girl	Tic-Tac-	And then … but make it to where the winning side or if it draws it's always the computer. The computer can never lose.	0	0	1	0	0	0	1	0	0	0
1	P7	women	S3 - girl	Tic-Tac-	There is a lot of methods in the internet	0	1	0	0	0	0	0	0	1	0
1	P7	women	S1 - girl	Tic-Tac-	A lot of what?	0	0	0	0	1	0	0	0	0	0

Clip Num	Activity	Team	PARTICIPANT	Activity	DIALOGUE	Self Regulation	Exchanging ideas	Giving directions	Justifying answers	Asking questions	Uptake	Decomposition	Pattern	Abstract	Algorithm
1	P7	men	S3_boy	Tic-Tac-	bro you still have to do it He lost by touch though	0	0	1	0	0	0	0	0	0	0
1	P7	men	S4_boy	Tic-Tac-	can we write the letter on one paper or should we use time	0	1	0	0	1	0	0	0	0	0
1	P7	men	S3_boy	Tic-Tac-	well dont you, dude if I looked that up that would be the answer	0	1	0	0	0	0	0	0	0	0
1	P7	men	S3_boy	Tic-Tac-	I mean unless you guys want to figure it out	0	0	0	1	0	0	0	0	0	0
1	P7	men	S3_boy	Tic-Tac-	Dont you have to play with a coin or some shit	0	0	0	0	1	0	1	0	0	0
1	P7	men	S3_boy	Tic-Tac-	like its never like the first move to me makers	0	0	0	1	0	0	0	1	0	0
1	P7	men	S2_boy	Tic-Tac-	so we just have to figure it out	0	0	1	0	0	0	0	0	1	0
1	P7	men	S2_boy	Tic-Tac-	fuck this test. What?	0	0	0	0	1	0	0	0	0	0
1	P7	men	S3_boy	Tic-Tac-	yeah play in the coner	0	0	1	0	0	0	0	1	0	0
1	P7	men	S2_boy	Tic-Tac-	Bottom or corner.	0	0	1	0	0	0	0	1	0	0
1	P7	men	S3_boy	Tic-Tac-	I don't think it	0	1	0	0	0	0	0	0	0	0
1	P7	men	S1_boy	Tic-Tac-	we still have to do it whoever goes first	0	1	0	0	0	0	1	0	0	0
1	P7	men	S2_boy	Tic-Tac-	we have to win	0	0	1	0	0	0	0	0	0	0

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