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BOARD # 199: Comparing Computational Thinking Learning and Engagement in First-Grade Boys and Girls: A Study of Algorithm Design and Debugging (Work-In-Progress)

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I hold a Ph.D. in Engineering Education and an M.S. in Computer Science, focusing on integrating computational thinking into pre-college education. My experience includes developing and implementing engineering and computer science curricula and actively participating in professional development for teachers to establish inclusive and innovative learning environments. At Purdue University's Center for Instructional Excellence (CIE), I work as a postdoctoral researcher, collaborating on faculty development, mentoring undergraduate students, and supporting curriculum initiatives.

My passion lies in promoting STEM education, advocating for increased participation in STEM fields. Alongside my primary research, I am interested in human-computer interaction, AI in education, educational robotics, and user experience (UX) design, focusing on how technology can improve teaching and learning for all learners.

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Comparing Computational Thinking Learning and Engagement in First-Grade Boys and Girls: A Study of Algorithm Design and Debugging (Work-In-Progress)

Introduction

Computational thinking (CT) is widely recognized as a core skill for 21st-century learners, essential for success in STEM fields. Despite efforts to promote STEM education, gender disparities persist, with women underrepresented in these fields. Scholars recommend early exposure to CT concepts in K-12 education to foster equity and inclusion [1]-[4]. Factors influencing the gender gap include cultural stereotypes, limited computing experience, and unequal treatment, leading to negative self-efficacy [5]-[8]. Positive engagement in STEM during early childhood can significantly influence long-term interest and participation. While several studies have examined girls' engagement with CT in grades 3-12, there is a lack of research on younger children. This study explores similarities and differences in CT engagement between first-grade boys and girls, contributing to inclusive STEM education by analyzing behavioral, cognitive, emotional, and social dimensions of engagement.

Theoretical and Empirical Context of the Research

The U.S. faces a shortage of skilled tech professionals, and exposing children to programming tools reduces learning barriers and increases interest [9], [10]. Computer science (CS) has a significant gender imbalance, with a decline in women's participation raising social justice concerns [11]. National data show only 15.5% of K-12 girls from historically underrepresented groups participate in CS courses, compared to 37.5% of all K-12 girls [12]. Stereotypes deter females from pursuing STEM careers, influencing behaviors and creating barriers to entry and retention [11], [13]. Expanding CS education beyond high school can increase the computing pipeline and change the path for young girls [12]. In this context, Computational thinking (CT) refers to a set of cognitive skills derived from fundamental concepts in computer science and has increasingly been integrated into K-12 curricula across the globe [14, 15]. Still, there is a lack of consensus on CT terminology, especially for young learners. Some categorize CT into dimensions like concepts, practices, and perspectives [16], [17], while others do not [18]. Views on CT vary; some see it as algorithmic thinking with automation tools (ISTE Framework), and others as practices involving computer tools (NRC, 2012, as cited by [19]). In this aspect, an increasing trend has drawn attention to CT activities involving algorithm design tasks and educational robotics [20]-[21]. One of the reasons is that coding games enhance children's problem-solving abilities, requiring strategic planning, self-regulation, and logical reasoning [22].

Despite this broad discussion, how preschoolers engage with CT is still obscure. Engagement is a construct with multidimensional and interrelated components, such as cognitive, behavioral, emotional, and social [23]-[28]. Scholars have included a social dimension in recent studies, consistent with Vygotsky's social constructivism theory [29]-[32]. The definition of student engagement varies, encompassing behavior, participation, emotion, investment, motivation, and reaction to challenge [23], [33].

Building on the understanding of engagement as a multidimensional and interrelated construct — including cognitive, behavioral, emotional, and social aspects—this study explores how preschoolers engage with CT. We complement our theoretical framework by drawing on the computational thinking (CT) definition proposed in [16]. This study took a comparative approach to examine potential differences in how boys and girls engage with CT, grouping participants by biological sex—boys, girls, and mixed-gender teams—and drawing conclusions based on observed engagement patterns. These observations focused on verbal language, interactions, and behaviors rather than relying on a predefined framework. This approach aligns with a social constructivist perspective, emphasizing learning through social interactions.

Therefore, we developed the MEST-CT (Model of Engagement in Sex-based Teamwork in Computational Thinking) framework to illustrate the multidimensional nature of engagement and the concepts and practices of CT (Figure 1). This framework incorporates the cognitive, emotional, behavioral, and social dimensions of CT tasks.

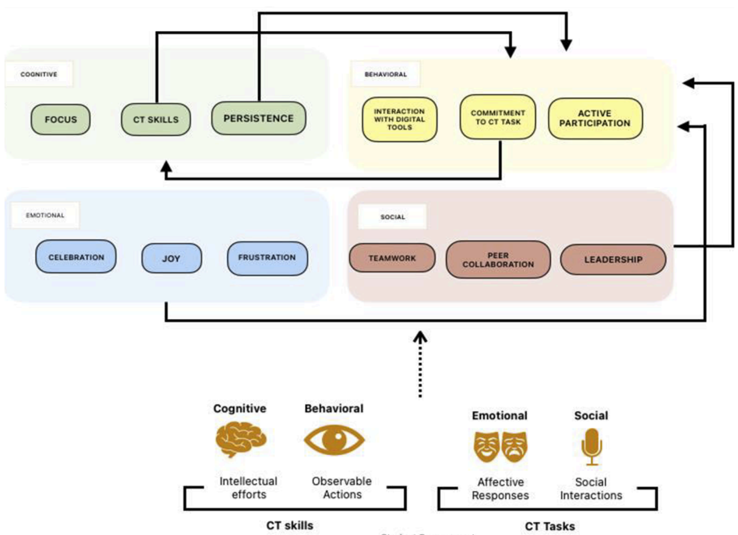

Fig.1. *Simplified Visual of the Model of Engagement in Sex-based Teamwork in Computational Thinking (MEST-CT).*

Methods

Study Design and Participants

This preliminary study explored the engagement of first-grade students in CT learning through educational robotics and block-based programming. Specifically, we examined how young learners interacted with CT tasks, considering cognitive, behavioral, emotional, and social dimensions of engagement. We also explored whether biological sex represented a strong reason for CT engagement differences. By observing students in their natural classroom environment, we could observe how engagement emerged through verbal language, collaboration, peer interactions, and teacher scaffolding. We aimed to answer the following research question: *What are the similarities and differences in how first-grade boys and girls engage with computational thinking (CT) through educational robotics and programming tasks?* Data were collected in a first-grade classroom at an urban Title I school. The sample included 9 students (4 boys, 5 girls) working in mixed-gender and same-gender teams. Informed consent and assent were obtained from all participants and guardians. Observations were conducted over 5 days in the students' regular learning environment to ensure validity. This method enabled an in-depth understanding of how engagement varied with team dynamics, learning styles, and individual traits. Researchers documented interactions through detailed field notes and video recordings, allowing for an iterative analysis process in which initial observations informed the identification of key themes.

Description of CT Activities

Students engaged in a structured sequence of CT tasks using educational robotics and block-based programming. We used a three-step approach to programming tasks: sequencing tasks, debugging, and finally incorporating loops. This progression utilized tools like the Robot Mouse, Tale-Bot, and ScratchJr to enhance students' computational thinking skills.

Robot Mouse introduced basic programming concepts through hands-on sequencing and debugging tasks. Tale-Bot extended these skills by incorporating patterns and loops, reinforcing computational thinking. Finally, students transitioned to ScratchJr, applying these concepts in a digital environment using block coding to create and execute programs. This structured progression ensured a gradual increase in complexity, engaging students in hands-on learning while reinforcing computational problem-solving skills.

Data Collection and Data Analysis

We conducted observations over five days, documented via field notes and video recordings. We analyzed student artifacts, including programming outputs and worksheets. Two researchers were involved in the data collection, which we call Researcher A and Researcher B. Students were organized in teams of three or four, each with iPads standing on each team desk to record their interactions while working on the coding challenges. During this time, Researcher B registered her observations with detailed notes on students' behaviors, interactions, and engagement. Students were organized into three or four teams, with iPads placed on each team's desk to record their interactions while they worked on the coding challenges.

Data analysis involved a multifaceted approach combining qualitative methods, emergent design, and inductive reasoning to identify themes and categories [34]. The study followed a structured coding scheme informed by the CT framework adapted from [16] and literature on student engagement. The engagement portion of the framework was further refined using emerging patterns from the data, helping define sub-themes for each engagement dimension mentioned in the literature. Additionally, we employed thematic analysis, memoing, and the Constant

Comparative Analysis [35] to develop a coding framework. We iteratively refined the code based on observed engagement behaviors, and our interpretations were guided by the research literature [36].

Preliminary Findings

The study followed a structured coding scheme informed by social constructivism, computational thinking, and engagement literature as a systematic approach to analyze how students engaged with CT activities. A structured checklist (e.g., persistence, hesitation, enthusiasm) was used to document engagement dimensions. This approach allowed for systematic observation without presupposing differences based on gender. One researcher initially coded behaviors, and a second researcher reviewed and discussed discrepancies for reliability. Table 1 categorizes teams as boys-only, girls-only, and mixed-gender based on team composition and their influence on collaboration styles. This team structure provided a foundation for examining engagement patterns across sex-based groups, allowing us to explore whether differences in CT engagement emerged based on team composition.
Cognitive engagement varied among students, with some using systematic approaches and others relying on trial and error. When analyzing whether a specific approach could be related to a particular gender, it was observed that these different approaches were seen for both genders. This suggests that these differences in cognitive engagement were not influenced by gender but could be linked to individual learning styles. Therefore, it was impossible to conclude that cognitive dimension differences were attributed to a specific gender group. Behavioral engagement was seen with all students actively participating, and their level of persistence varied based on task complexity with no indicators of sex-based causes. Instead, behavioral engagement was influenced by their cognitive, emotional, and social interactions (Table 1) rather than sex.

Table 1
Examples of Computational Thinking Engagement across the Sex-based Teams

Team	Student	**Cognitive** *CT understanding and application*	**Emotional** *Feelings during CT tasks*	**Social** *Interaction and collaboration*	**Behavioral** *Overall engagement across dimensions*
Boys	George	Strong grasp of sequences and debugging. Systematic problem-solving.	Positive emotions during success, easily frustrated by errors.	Leader, strong collaboration with Trevor, supported Jonathan. Resolved conflicts quickly.	Active participation, initiative in proposing solutions, persistent.
	Trevor	Engaged in problem-solving, used trial-and-error. Struggled with paper-based tasks.	Excited during success, frustrated by errors.	Collaborative, supported George but was passive with Jonathan. Minor conflicts with George.	Highly committed to coding, less focused on paper tasks. Persistent.
	Jonathan	Struggled with problem-solving, effortful but confused.	Frustration when left out, disengaged emotionally when struggling.	Often isolated, struggled with social interaction. Avoided conflict.	Inconsistent focus, often gave up when challenged.
Girls	Isabella	Strong in pattern recognition, sequencing. Struggled with debugging loops.	Positive during success, frustrated by conflicts.	Assertive, balanced cooperation with assertiveness. Conflicted with October.	Committed, persistent but less methodical.
	Carmen	Strong in sequencing and loops, occasionally needed assistance.	Positive emotions, more reserved compared to peers	Independent but collaborative, acted as a mediator between Isabella and October.	Focused, persistent in troubleshooting. Consistently engaged.
	October	Strong in sequencing, patterning, and debugging.	High emotional investment, frustration with peers' struggles.	Leader, often took control but was collaborative. Conflicted with Isabella.	Persistent, proactive in all tasks. Always engaged.
Mixed	William	Strong in basic sequences, struggled with abstraction and loops.	Positive but frustrated when overshadowed.	Primarily a follower, patient in conflicts with Amelia. Cooperative with Joana.	Proactive, eager to contribute. Persistent despite challenges.
	Amelia	Engaged but relied on trial-and-error. Strong in sequencing.	Positive during success, often frustrated and impatient.	Domineering, frequently conflicted with William. More cooperative with Joana.	Persistent, task-oriented, resilient despite conflicts.
	Joana	Methodical, strong in problem-solving and sequencing.	Positive, emotionally stable. Empathetic.	True leader, mediated conflicts between Amelia and William.	Proactive, consistent, and persistent. Guided the team effectively.

Likewise, emotional responses such as excitement and frustration varied among students regardless of gender, as their emotional reactions were observed with girls and boys. For instance, one boy exhibited frustration and disengagement when he struggled with a CT problem, while his male peers demonstrated persistence and problem-solving interest. Similarly, some girls displayed excitement and frustration while working through coding challenges, aligning with the variation seen among boys. This suggests that boys and girls express emotions such as frustration, hesitation, and enthusiasm, representing their equal emotional investment in CT tasks.

Social engagement was evident in collaboration styles across teams. Students with more proactive personalities naturally took leadership roles, regardless of sex. That means girls and boys were seen playing leadership-follower roles. This seemed to depend on their personality traits rather than their gender. Additionally, variations in engagement were observed based on team composition, with some students thriving in collaborative settings while others displayed hesitation, which is not conclusively linked to biological sex.

Overall, we could not find evidence that supports the claim that differences in engagement in computational thinking were connected to gender. Instead, struggles and strengths in learning and engaging with CT tasks emerged in both sex-based groups. Minor variations in engagement or learning between boys and girls could be due to natural cognitive, social, or emotional development typical of young children rather than inherent gender-based differences.

Conclusion

This study examined similarities and differences in how first-grade boys and girls engage with computational thinking (CT) through educational robotics and programming tasks. Engagement patterns were broadly comparable across cognitive, behavioral, emotional, and social dimensions. Preliminary findings show that boys and girls demonstrated equal engagement patterns across dimensions. This conclusion suggests that variations in engagement were linked to other factors rather than gender. These factors could include learning styles, personality traits, and personal preferences. Team dynamics could also have influenced their engagement, with some students thriving in collaboration settings.

In contrast, others would have better opportunities to engage if they could follow their own pace with minimal interference from other team members. These distinct characteristics were observed with boys and girls, suggesting that CT engagement at this early age could be influenced by different learning styles and personality traits rather than gender. There was no evidence to conclude any CT engagement differences connected with gender. This could be because students at this early age could have had minimal exposure to gender stereotypes. However, conducting future studies to confidently draw such conclusions is crucial.

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