ASSESSING COMPUTATIONAL THINKING THROUGH LEARNERS' EMBODIED INTERACTIONS AND THE LENS OF COMPLEX DYNAMICAL SYSTEMS THEORY

by

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(Under the Direction of Theodore J. Kopcha)

ABSTRACT

The purpose of this dissertation is to explore how different methodological possibilities can support the analysis of computational thinking (CT) from an embodied perspective. To that end, this dissertation first presents an approach to multimodal transcription using a methodological framework that aligns with the study of CT as an embodied phenomenon. The framework, which incorporates a social semiotic approach to multimodality, then is applied to the same multimodal transcript using three different analytical approaches: (1) a grounded approach, (2) a process of transduction with a priori coding and thematic analysis, and (3) an artificial intelligence (AI) pattern recognition approach. Each approach is presented as a case, allowing each to be evaluated within as well as across approaches. The criteria for evaluation include two major characteristics of embodied cognition and complex dynamical systems: self-organization and emergence (Gallagher & Appenzeller, 1999; Richardson & Chemero, 2017). This research contributes meaningfully to current and ongoing questions about embodied cognition in that it identifies the strengths and weaknesses associated with different approaches to the analysis of CT from a social semiotic perspective of multimodality.

INDEX WORDS: Computational thinking, Dynamical systems theory, Social semiotic approach to multimodality, Educational robotics, Extended cognition, Embodied interactions

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DEDICATION

This dissertation is dedicated to my beloved parents, Birsen Ocak, Şahin Ocak, and to my precious sister, Seren Ocak. I love you all so much; you mean the world to me.

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CHAPTER 1

Introduction

Recent perspectives of embodied cognitive science offer new methodological prospects for exploring children's computational thinking (CT), where computational thinking is studied as a process rather than a product of learning. Quasi-experimental research is a common approach to studying CT, often relying on standardized testing to assess CT skills (e.g., Román-González, 2015; Sung et al., 2017). Quasi-experiments, however, are built on the notion that learning is an activity that is "static, predictable, and ultimately tend towards a state of equilibrium, stillness, inactivity" (Davies, 1976, p.281). This view largely ignores current perspectives of CT, which suggest CT is a chaotic and self-organizing process rather than a "linear sequence of procedures" (You, 1993, p.20). Standardized testing, then, fails to capture the dynamic aspects of CT because it is designed to measure "continuities of systems behavior" (p.27) rather than the chaotic, self-organizing aspects of the process. This highlights the need for robust tools and understanding CT that entails moving away from positivist stance, which tends to reduce CT to a matter of testing of specific computer programming or mathematical skills.

At the same time, embodied perspectives also present methodological challenges. Although some scholars have begun studying CT from an embodied perspective (Chiu et al., 2018; Chung & Hsiao, 2019; Black et al., 2012; Grover & Pea, 2013; Lu et al., 2011; Melcer, 2017; Sung et al., 2017), little is known about how embodied perspectives can be leveraged into a research methodology in the area of CT (Grover & Pea, 2013; Kopcha & Ocak, 2019). Overall, attempts to conceptualize CT from an embodied perspective have not translated into researchers' methodological preferences (Chiu, Wauck, Xiao, et al., 2018; Chung & Hsiao, 2019; Melcer et al., 2018; Sung et al., 2017). This has led to a growing interest in the literature on describing and assessing students' CT from an embodied perspective.

The purpose of this dissertation is to explore how different methodological possibilities can support the analysis of computational thinking (CT) from an embodied perspective. To that end, this dissertation first presents an approach to multimodal transcription using a methodological framework that aligns with the study of CT as an embodied phenomenon. The framework, which incorporates a social semiotic approach to multimodality, will then be applied to the same multimodal transcript using three different analytical approaches: (1) a grounded approach, (2) a process of transduction with a priori coding and thematic analysis, and (3) an artificial intelligence (AI) pattern recognition approach. Each approach will be presented as a case, allowing each to be evaluated within as well as across approaches. The criteria for evaluation will draw from two major characteristics of complex dynamical systems that are foundational to embodied perspectives of cognition: self-organization (i.e., unordered patterns that emerge from interaction) and emergence (i.e., an underlying, yet covert order operates in the system) (Gallagher & Appenzeller, 1999; Richardson & Chemero, 2017). This research contributes meaningfully to current and ongoing questions about embodied cognition in that it will identify the strengths and weaknesses associated with different approaches to the analysis of CT from a social semiotic perspective of multimodality.

This dissertation focuses on computational thinking (CT) because CT has gained immense popularity in a diverse range of fields over the last few decades (Brennan & Resnick, 2012). CT is most commonly defined as 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" (as cited in Wing, 2010, p. 1). Wing's (2006) influential article, *Computational Thinking*, is among the first since Papert's (1980) introduction of the Logo Turtle to play a major role in bringing CT to K-12 education. Wing's (2006) article has been influential for highlighting the significance and benefits of learning computer science for younger kids. Since Wing's (2006) introduction of CT to K-12 , CT has been extensively described in the literature as a frame and a sum of skills that refers to the ways in which computer scientists approach problems (Denning 2009; Sands et al., 2018; Wing, 2006). There is strong agreement in the existing literature that CT is an essential set of 21th-century skills for its proven benefits ranging from an improved understanding of computer programming, problem-solving, and even attitudes towards STEM careers (Chalmers, 2018; Doleck, Bazelais, Lemay, et al., 2017; ISTA, 2014). Scholars and educators, therefore, view CT as a powerful perspective on problem-solving that can help address current teaching and learning complexities in K-12 education.

The term, computational thinking, was coined nearly half a century ago (see Pólya, 1945; Perlis & Thornton, 1960). Since then it has been applied to problem-solving and computer programming (e.g., Papert, 1980) and other STEM disciplines (Brennan & Resnick, 2012). While the scope of CT has been scrutinized and/conceptualized in different fields (e.g., informatics, science), its description, nature, and assessment have developed through ongoing scholarship and a persistent interest from the field of computer science (Tedre & Denning, 2016). Over the years, researchers have offered a variety of CT definitions (Aho, 2012; Barr et al.; 2011); however, no agreement has yet been reached on how to describe CT and its pertaining cognitive skills (Brennan & Resnick, 2012; Mannila et al., 2014).

Even though CT was initially associated with computing and programming, numerous attempts have been made to demarcate CT from programming (National Research Council [NRC], 2010; see also Papert, 1980; Yaşar, 2018). According to Kong et el. (2019), the importance of distinguishing CT from its related skills (e.g., computer programming, information processing) dates back to Papert (1980), who argued that programming was just a context for applying CT. Building on Papert's (1980) inquisition, Lu and Fletcher (2009) later inquired about the degree of programming knowledge necessary for excelling at CT; they similarly found that computational thinking is not the equivalent of programming. To address this distinction, great effort has been made to define CT and its underlying skills to foster computer science (CS) literacy (Aho, 2012; Berland & Wilensky, 2015; Cuny et al., 2010; Grover & Pea, 2013).

The skills inherent in CT fall within a wide spectrum of options that depend on the researchers' conceptualization and understanding of CT. These conceptualizations are informed by how a researcher positions him or herself epistemologically. In a systematic analysis of the different characterizations of CT, Shute et al. (2017) claimed that CT could not be narrowed down to a unified entity since CT is a growing body of knowledge. Yet, still, the commonalities among the characteristics of CT exist and can be summarized under five major components: abstraction, pattern recognition, decomposition, algorithmic thinking, and debugging (Anderson, 2016; Yaşar, 2018). These characteristics often involve skills that emerge while solving a problem using a computational device (Yaşar, 2018). Likewise, Shute et al. (2017) claim that CT comprises similar characteristics with two additional features: iteration and generalization. Others have characterized CT as involving a variety of skills, ranging from working with different levels of abstraction to decomposing large tasks into smaller sub-goals and using pattern recognition and algorithmic thinking to develop efficient and precise solutions (Denning, 2009; Wing, 2010).

One of the persistent questions in CT research is how to assess such a complex, multi-layered phenomenon; the problem becomes even more conspicuous in the context of K-12. Since the introduction of CT to the education research by Wing (2006), educational scholars, researchers, and policy-makers have sought ways to assess CT skills in today's schools (Tedre & Denning, 2016). However, current methods for evaluating student's CT have been criticized for reducing CT to children's ability to successfully complete a task or execute specific computer programming skills (Shea & Duncan, 2013). At the same time, ambiguity among the various constructs associated with CT has led to a growing discrepancy in the literature on how to study and assess students' CT (Tenre & Denning, 2016). While such studies are important, there is a growing call for another body of research - one that focuses on computational thinking as a learning process rather than a product of that process (Berland & Wilensky, 2015; Shea, & Duncan, 2013).

The recent focus on CT as a process is due to recent perspectives that describe CT as a complex, dynamic phenomenon (Berland & Wilensky, 2015; Kopcha & Ocak, 2019). Kopcha and Ocak (2019) have described how CT develops in a discontinuous fashion in which learners adapt and/or self-organize their environment as a result of their feedback based interactions with the environment. If CT is framed as a complex, dynamical system, however, then the methodological tools for measuring CT should be compliant with those characteristics. Jacobson et al. (2020) cited Bereiter and Scardamalia (2005) to underscore this urgent need for methodological tools to study dynamicity in education research:

> Self organization and emergence … [in] mainstream educational psychology … [make it] increasingly apparent that there are no simple causal explanations for anything in this field" and "learning itself, at both neural and knowledge levels, has emergent properties (Jacobson et al., 2020, p. 112)

As the quote suggests, self-organization and emergence are two important characteristics of complex, dynamic systems. Self-organization reflects a sort of synergy within a system, where unordered patterns emerge from the interaction within the system. Those patterns are not linear and predictable; rather, they emerge according to an underlying yet covert order within the system (see also Gallagher & Appenzeller, 1999; Richardson & Chemero, 2017). Hence, Jacobson et al. (2020) are suggesting a move away from making predictions based on the causal relationship between the variables in educational complex systems. This encourages researchers to look for more naturalistic and phenomenological approaches that reveal how cognition emerges and organizes through the use of one's body and interaction with the environment.

One powerful and promising way to evidence children's CT is to understand how CT emerges and develops through interaction with the people and tools in the learning environment (Black et al., 2012; Grover & Pea, 2013; Kopcha & Ocak, 2019; Lu, Kang, Huang, & Black, 2011; Sung et al., 2017). This perspective treats CT as part of a dynamical system. A dynamical system is ever changing; the components of that system (e.g., learner, tools, other people) both influence *and* are influenced by a learner's actions (Richardson & Chemero, 2014). Framing this type of interaction as embodied participation, Goodwin (2007) suggested that learning is the product of the "collaborative actions of multiple parties, and structure in the environment" (Goodwin, 2007). These actions are, by nature, embodied in that they are grounded in one's experiences and reactive to the ongoing changes in the environment. In the context of CT, this perspective suggests that learning goes beyond an accurate or successful construction of a computer program. Learning is also evident in the types of CT skills that emerge over time in a given environment, and the way that children's understanding of those skills becomes associated with their own bodily experiences.

For Jacobson et al. (2019), the literature has remained insufficient to offer methodological tools while studying major key features of complex systems: non-linearity and emergence. They further went on to note that it is crucial for researchers to interrogate how promising the tools and/or methodological techniques are to understand complex systems in education research.

The overall purpose of this dissertation therefore is to explore different methodological possibilities that can support the analysis of video data that examines computational thinking (CT) from an embodied perspective. From embodied perspective, the meaning behind CT develops with and through a variety of modes that are co-constructed by the participants. As the different modalities become present, the social and cultural aspects of a phenomenon are formed through both verbal and non-verbal characteristics (Goodwin, 2010; Streeck et al., 2011). Social semiotic approaches to multimodality would therefore highlight the interdependency of various modes that contribute to learning during children's robotics activity (Jewitt et al., 2016).

In this study, two fifth-grade participants were video recorded as they completed an educational robotics activity. 100-minute video data were first transformed in a multimodal transcript using Bezemer's (2014) approach to multimodal analysis. Because Bezemer draws on social semiotics, his approach focuses on understanding the meaning that is constructed through human interaction, both with other people as well as the structures in the environment. Such interactions can be revealed in many forms, including dialogue, gestures, tool use, and body movements. This has the potential to reveal nuanced details about children's computational thinking during educational robotics.

Although Bezemer's (2014) approach provides a structure to guide creating and analyzing multimodal transcripts, researchers may approach that analysis in different ways. In fact, researchers' choices throughout the design and creation phase of the multimodal transcript is a significant part of the data analysis process in multimodal research (Baldry & Thibault, 2005; Helm & Dooly, 2017). Whereas some might focus on how physical interaction helps reveal the meaning behind a phrase or utterance (e.g., Flood & Abrahamson, 2015; Nemirovsky, & Ferrara, 2009), others might apply methods that attempt to look across modes at the same time (Mavers, 2012). Bezemer's approach is not prescriptive—several different forms of analysis might fit under the larger methodological framework of multimodality and social semiotics (e.g., multimodal transcription). As a result, researchers are left to determine for themselves the strengths and weaknesses associated with different analytical approaches. Thus, this study seeks to identify those affordances and limitations using criteria relevant to embodied perspectives of cognition.

This study explores three different analytical approaches to the analysis of multimodal transcripts: (1) a grounded approach to analyzing the multimodal transcript, (2) a process of transduction using a priori codes and thematic analysis, and (3) an artificial-intelligence-enhanced pattern recognition approach. By treating each approach as a unique case, this research will look within and across cases to offer scholars a better understanding of different approaches to multimodal analysis and its application in the study of CT in young children. The overall question that guides this research is: *How can embodied perspectives be leveraged into a* *research methodology in the area of computational thinking?* To answer this question, I will first look within each of the three different approaches to answer these sub-questions:

1. How does a grounded approach to analyzing a multimodal transcript approach the study of children's CT as an emergent and self-organizing phenomenon?
2. How does a process of transduction with a priori coding and thematic analysis approach the study of children's CT as an emergent and self-organizing phenomenon?
3. How does an AI-enhanced pattern recognition approach approach the study of children's CT as an emergent and self-organizing phenomenon?

While these questions are important, the ultimate goal of this study is to compare the results of each approach to determine the strengths and weaknesses of each when used to understand children's CT through their embodied interactions. Thus, the final question was:

4. What are the key strengths and differences associated with the three different approaches to the multimodal analysis of children's CT?

Definition of Key Terms

- *Computational thinking.* Such thinking incorporates several problem-solving skills inherent in computer science, from decomposing large tasks into smaller sub-goals to using pattern recognition and algorithmic thinking to develop efficient and precise solutions.
- *Dynamical systems.* Dynamical system theories focus on modeling temporal organization of the behavior as it changes over time (Hotton & Yoshimi, 2010).
- *Educational robotics.* Educational robotics involves children to successfully complete a task or execute specific computer programming skills.

- *Mode.* A set of semiotic assets are used by the participants for meaning-making. Modes are made up of "actions and artifacts we [human beings] use to communicate" (Van Leeuwen, 2005, p.3). This includes but not limited to participants' tool use, gestures, spoken words, etc.
- *Multimodality.* Multimodality refers to the data that involves more than one mode of communication (e.g., linguistic, numerical). This includes both verbal and non-verbal aspects of interaction that provide insight into one's thinking, such as peer-to-peer (e.g., discourse, gesture) and peer-to-tool (e.g., robot, computer) interactions.

CHAPTER 2

Literature Review

Even though the origins of computational thinking (CT) in education research can be traced back to Papert (1980), Wing (2006) popularized CT as a term in the field of teaching & learning. According to Mannila et al. (2014), both Papert and Wing were aware that CT is much more than the ability to use a computational device, but instead a powerful method of thinking in problem-solving. Today, the majority of countries aim at building a workforce that excels at CT skills to secure a better place in the most innovative economies (NRC, 2010; Shute et al., 2017). CT is therefore considered a necessary 21st-century skill set for everybody, not just computer scientists (Curzon et al., 2009; NRC, 2012; ISTA, 2014). This has led educational scholars, researchers, and policy-makers to find ways to introduce and improve CT skills in today's schools.

One of the powerful and trending ways to study CT lies at its intersection of embodied cognition and the analysis of learners' multimodal interactions. Embodied cognition is viewed as an opportunity to address ongoing issues in CT education because embodied perspectives focus on the role of one's bodily experience in learning (Chiu et al., 2018; Chung & Hsiao, 2019; Fadjo, 2012; Grover & Pea, 2013; Lu, Kang, Huang, 2011; Melcer, 2017; Sung et al., 2017). To that end, this literature review first traces the historical roots of CT that shape current perspectives. Next, I briefly introduce the philosophical and theoretical underpinnings of EC that shed light on how embodied perspectives can be leveraged into a research methodology to understand children's CT through their embodied interactions. Those underpinnings begin with an understanding of the essence of computational problem-solving, which serves to explain how CT is a complex, dynamical system that is composed of nested, interacting subsystems. Finally, I explain how new research on CT led scholars to explore new avenues for studying CT.

An Overview of Computational Thinking

The notion of using computational thinking (CT) in K-12 research dates back nearly three decades, the very notion of which was articulated by Seymour Papert, in his seminal book *Mindstorms* (1980). Since the first proposal of CT, the description and constructs associated with CT entails has been under scrutiny. Wing (2006) initially described CT as “solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science (2006, p.33). It was not until the publication of her influential article that CT gained real momentum in K-12 education. Wing highlighted that CT is a sum of skills to add to a child’s toolkit. Prominent scholars of education, learning sciences, and computer science were intrigued by the Wing’s (2006) proposal. Following the growing interest towards CT, two National Academy of Science workshops were held to discuss characteristics of CT and its implications for teaching and learning (see Grover & Pea, 2013; National Research Council [NRC], 2010).

After the conventions, Cuny et al. (2010) reshaped the definition of CT and it became one most influential and widely adopted in the field of education and learning sciences in which the authors construed CT as “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” (as cited in Wing, 2010, p. 1). Other researchers have drawn on Wing’s work to craft a variety of different definitions, either revising or making slight changes to its original (Barr et al., 2011). For example, Aho (2012) described CT as “thought processes involved in formulating problems so their solutions can be represented as computational steps and algorithms." Moreover, the Computer Science Teachers Association (CSTA, 2017) defines computational thinking as "thinking about data and ideas, and using and combining these resources to solve problems." Even though a variety of CT definitions are proposed in the preceding literature (Barr et al., 2011; Berland & Wilensky, 2015; Ching et al., 2018; Israel et al., 2015), no single, agreed-upon definition of CT has been made. This suggested that neither the description of CT nor the skills it pertains can be generalized (Shute et al., 2017). Based on the authors' descriptions above, such thinking incorporates several problem-solving skills inherent in computer science, from decomposing large tasks into smaller sub-goals to using pattern recognition and algorithmic thinking to develop efficient and precise solutions. This suggests that the skills that are associated with CT are derived from its description, which explains the construct ambiguity that is inherent in the CT literature.

History of Computational Thinking

The place of computing in a diverse range of fields has been scrutinized since the 1950's—whether it belongs to mathematics, engineering, or if it is an interdisciplinary field (Fein, 1959; Gorn, 1963; Dijkstra, 1974; see Tedre & Denning, 2016; Zadeh, 1968). These discussions helped computational thinking gain a unique identity under an emergent research field called "computer science" over the decades that followed (Dijkstra, 1974). It did not take long to observe a snowballing reaction to teach computation at the college level. In 1962, Alan Perlis claimed that learning how to program is a worthwhile goal for every learner, so it has to be a part of educational institutions (as cited in Guzdial, 2008). As do many others (Dijkstra, 1974; Knuth, 1974), Perlis further argued that information processors were "general-purpose mental tool", which suggested computing is much more than the ability to use a computer. He also strongly associated CT with algorithmic thinking and claimed it as an essential thought process for every learner (see Caeli & Yadav, 2019). However, translation of Perlis' (1960) notion of "general-purpose mental tool" into a pedagogy had been challenging for the reasons of lack of exemplary models in computer literacy.

Within the next decade, CT became recognized as a separate discipline—a discipline that featured a unique way of thinking that translates problem-solving processes into a computer language (see Tedre & Denning, 2016). Since this involved a step-by-step design to solving a problem, algorithmic thinking was seen at the heart of CT in the 1970s. Not surprisingly, the next decade, the 1980s, was spent on the notion of how CT was not only made up of algorithmic thinking or programming (Papert, 1980). The scholars later broadened the extent of CT to cover the design aspect and systems architecture, in other words designing for the environments that algorithms could properly work. Overall, debates in the 1970-80s were shaped around the place of algorithmic thinking in CT, and its defining characteristics. However, the literature remained insufficient to unveil cognitive mechanisms behind the development of CT.

Embodied Roots of Computational Thinking

As argued above, the integration of computational thinking into education is not a new idea. Perlis (1962) took the initiative and claimed that learning how to program was a worthwhile goal for every learner, so it has to be a part of college education (as cited in Guzdial, 2008). Along similar lines, Minsky (1970) highlighted the significance of programming; it should be taking precedence over mathematics in early education. Back then, researchers believed that learning how to program would be a contributing factor to the development of other cognitive skills (see Voogt et al., 2015; Sung et al., 2017). Therefore, programming had an enormous potential to transform education for leading the development of higher-order mental skills. In this context, the baby steps to translate CT to K-12 education were taken with the pioneering ideas of Papert. Papert (1980, p.155) collaborated with Piaget to teach children a computing language (i.e., Logo); they believed that learning how to program would make an in-depth intellectual contribution to a learner's mindset. Both Perlis (1962) and Papert (1980, 1981) agreed that learning through a tool was a way of improving intellectual capacity; the very notion of which was grounded in the similar pedagogical approach towards computers that is "*an object to think with*." (see Resnick et al., 1996, p.449).

For some, Piaget's (1952) research is seen as the roots of sensorimotor contingencies theory (SCM). As cited in Pezzulo (2015), Piaget was the first who claimed that action contributes to the development of cognitive activity. Piaget's genetic epistemology was influential in that it prioritized learners' interactions with the environment for cognitive development (see Wellsby & Pexman, 2014). Piaget's (1971) work influenced later scholars to lead to the idea of embodied action (Reinholz et al., 2010). Therefore, Piaget's (1971) genetic epistemology was seen consequently as the forerunner of action-oriented and embodied theories of cognition, and his collaboration with Papert was ground-breaking in a sense that opened a new perspective on how children learn by using computational tools.

Papert's Logo turtle (i.e., robot) can be seen as a precursor of the movement that adopts the implications of embodied cognition to learning in that the manipulation of the turtle contributes to childrens' intellectual development. From an embodied perspective, cognition is extended to the objects and/or tools in the environment (Clark & Chalmers, 1998). Manipulation of objects facilitates learners' skills of spatial visualization and helps ground knowledge in their bodily experiences (Reinholz et al., 2010). Moreover, tools play a central role in recognizing new affordances (i.e., opportunities for action) in the environment (Hirose, 2011). Accordingly, Papert's notion of an "object to think with" is profoundly aligned with one of the central tenets of embodied cognition; external manipulation of tools helps extend learners' perception (Liben, 2012). Therefore, Papert (1980) proposed "analogizing oneself to a computer" (p.155) as a powerful learning strategy. Likewise, recent research in K-12 supports the findings that embodying and/or acting out an external agent (e.g., educational robots) helps increase conceptual understanding (Lu et al., 2011; Sung et al., 2017).

As in many other fields as research on gesture in mathematics or other areas attest that children draw on their bodily understanding of the world when engaging in CT (Abrahamson, 2017; Ferrara, 2014; Liben, 2012). Accordingly, several different attempts have been made to introduce CT to K-12 education, the activities that are commonly associated with educational robots. Educational robots are tools that serve as an embodied agent of children's abstract thinking, and through their manipulation, learners' mentality becomes linked to a physical world. This is often evidenced through learners' multimodal embodied interactions with technology (i.e., the robot). As a consequence, embodied cognition gains particular importance during robotics activity because the robot provides direct feedback as it executes various commands, which helps young children bridge abstract concepts through a concrete representation of their CT (Sung et al., 2017). This is an essential component of embodiment—that is, the "body's feedback-driven role" in cognition (Wilson & Foglia, 2011, p. 8)—that is associated with the computational thinking needed for children to program a robot.

At this time, scholars are interested in studying CT from an embodied perspective (e.g., Fadjo, 2012; Grover & Pea, 2013; Kopcha et al., 2020; Lu et al., 2011; Sung et al., 2017). For example, Fadjo (2012) explored CT from a sensorimotor account; the enactment of coding arrays (i.e., perspective taking of embodied agents) offered empirical evidence that bodily movement facilitated learning CT in K-7 education. The author also explored how physical manipulation of external devices enhanced the abstract-concrete relationship. Sung et al. (2017) similarly combined these different perspectives of embodiment to explore children's CT. In their study of 37 second-grade children, the participants who used their bodies to conceptualize the robot's movement were more successful at completing new problem-solving tasks and using block-programming to navigate the robot. More recently, others have begun to address the role of embodied interactions (e.g., gestures) that emerge at different phases of CT, such as abstraction and debugging (Chiu et al., 2018; Chung & Hsiao, 2019; Kopcha & Ocak, 2019; Kopcha et al., 2020). For example, Kopcha and Ocak (2019) studied how computational thinking was embodied for a pair of 5th-grade children during a collaborative robotics education activity. Their research suggests that children use their bodies and the structures in the environment to create new and novel approaches to decomposing the robot's movement and programming it with mathematical precision (i.e., algorithmic thinking). Overall, these studies suggest that embodied perspectives are a powerful and promising way to understand how CT develops through interaction with the people and tools in the learning environment (Fadjo, 2012; Grover & Pea, 2013; Lu et al., 2011; Sung et al., 2017). This is particularly relevant in K-12 education, where there is a growing call for research that moves away from current approaches to more robust tools and methods of understanding CT.

Current Concerns and Areas of Emphasis

Since the introduction of CT by Wing (2006), educational scholars, researchers, and policy-makers have sought ways to introduce and improve CT skills in today's schools; this is commonly associated with computer science activities (Tedre & Denning, 2016). National initiatives (e.g., US Dept. of Education, International Society for Technology in Education

[ISTE]) continue to emphasize the importance of developing children's computer science and computational thinking skills in today's schools (NRC, 2010/2018). For K-12 education, the foundations like the American Computer Science Teachers Association (CSTA), ISTE, code.org, and K12CS.org issued guidelines on how to describe and integrate CT to in and out-of-school curriculum (Mannila et al., 2014; Tedre & Denning, 2016).

For Denning (2009), however, proposing guidelines was too limiting in terms of the teaching and learning complexities in K-12 settings (Barr & Stephenson, 2011; Mannila et al., 2014). Denning's concern was that a step-by-step, one-size-fits-all approach for the development and integration of CT in educational settings would not be feasible. As a result, there are now multiple and, at times, divergent ideas about the ways in which CT should be adopted to educational environments, particularly in K-12 (Román-González et al., 2019). In fact, researchers have recently been embracing more innovative approaches to explore the complex nature of CT. For example, Berland and Wilensky (2015) combined complex systems theory with computational perspectives to unfold learners' understanding of computational content. The authors went on the note that CT is a complex and highly contextual phenomenon; it is a body of knowledge that is sensitive to how one reacts to a particular problem.

One of the other persistent issues in CT research is how to assess such a complex, multi-layered phenomenon; the problem becomes more conspicuous in the context of K-12. For example, Grover & Pea (2013) noted how a lack of proper CT assessment impedes the process of efficient CT integration to K-12 curriculum. Similarly, Buffum et al. (2015, p. 622) highlighted the urgent need for a standardized approach to measuring learners' CT. In response to this call, Román-González (2015) developed one of the key psychometrics tools that aimed at measuring CT for middle schoolers (i.e., Computational Thinking Test (CTt)). Others have similarly underlined the need for CT-related assessment tools for K-12 (Brennan & Resnick, 2012). These tools ranged from multiple-choice tests (Weintrop & Wilensky, 2015), student artifacts (Bers et al., 2014; Koh et al., 2010; Werner et al., 2012) to Likert scales (Atmatzidou & Demetriadis, 2016).

Table 2.1 summarizes the current approaches to assessing CT as an embodied phenomenon. One commonality between the studies listed below is their overemphasis on the product of learners' CT over the process. This is evident from the researchers' methodological preferences (i.e., experimental designs), which tend to conflate embodied cognition synonymously with bodily movement. This conflation reduces a complex phenomenon to a degree of movement, which is problematic embodied perspective in that it fails to account for the reasoning behind such movement.

Table 2.1

Analysis of Recent Research on CT As an Embodied Phenomenon

	Purpose	**Hypothesis of EC**	**Methodology**	**Field of Study**
Melcer and Isbister (2018)	To explore the impact of embodied interaction with tangibles and use of a mouse during play on CT.	Use of tangibles has positive learning outcomes.	**Mixed:** 2x2 between-subjects factorial design combined with the short interviews and field observations.	Engineering Education Research

Sung et al. (2017)	To explore the efficiency of two full embodied vs. low embodied instructional design.	Physical enactment of computer programming enhances conceptual understanding.	**Quantitative:** 2x2 between-subjects factorial design to compare and contrast the efficiency of different instructional strategies.	Education Research
Chung and Hsiao (2019)	To inform the design of learning environments that utilize gestures in augmented reality application.	An augmented reality application that utilizes gestures provides learning benefits.	**Qualitative:** Interviews and observation to explore students' attitudes toward the use of AR and embodied learning for CSE.	Engineering Education Research

For example, Sung et al. (2017) explored the effect of full versus low embodiment instructional design on conceptual development through a 2x2 factorial design. The authors characterized full- versus low-embodied condition in terms of the degree of bodily engagement; learners using whole-body movements (i.e., role-playing) were expected to outperform their hand-gesturing pairs. Categorization of embodiment in terms of the degree of bodily engagement undervalues the significance of other types of multimodal interactions, particularly the impact that arises from the interplay of different semiotic assets (i.e., language, gestures, and environmental structures) (Goodwin, 2007).

In another example, Chung and Hsiao (2019) similarly hypothesized that the inclusion of sensorimotor interactions in an augmented reality application would support CT skills like debugging and abstraction. In their design, the authors tracked the students' finger movements when simulating a helicopter. The authors underlined the need for quantitative gesture analysis (i.e., quantitative data collection) to understand the function of gestures. They intend to devise a behavioral gesture analysis for future research that evaluates “task completion time, number of actions (e.g., rotation, swipe), number of errors, and the time to complete the tasks” (p.38). In their study, the authors underscored the need for complementary, quantitative data to decide the tool’s feasibility. This need underscores the context-dependent feature of gestures, which requires a researcher to understand both *what* gestures are used by participants and *why*.

Melcer and Isbister (2018) likewise explored the impact of embodied interaction with tangibles during play on CT learning. The embodied interactions involved the play with the mouse and tangibles. The authors studied the learning outcomes through pre-post performance tasks that were analyzed using a 2x2 between-subjects factorial design. The authors’ approach to embodied interaction focused on the human-tool interaction (e.g., mouse versus tangibles), but lacked attention to the interplay of the modes in the broader social context.

Even though these studies lean towards accepting that movement contributes skill development (i.e., *action before concept*), the research designs associated with each are reductive. The methods make embodiment synonymous with the bodily movement, which can be counted and quantified. This results in a methodological tendency to associate the efficiency of learning outcomes with how much body is involved in the instruction (e.g., low versus full embodiment; mouse versus tangible). One possible shortcoming of such reductive perspectives is that it undervalues the body’s ongoing reaction to its environment. Embodiment is not just the movement of a body; rather, it focuses on how mind, body, and environment work together as a complex system of cognition and reasoning. Thus, reducing embodiment to the amount or type of movement misses the point of embracing an embodied perspective of CT because it continues to focus on the product of CT rather than the process. Embodied interactions contain a wealth of information that are revealed through the interplay of semiotic resources. Thus, the study of CT would benefit from methods that focus on understanding the interplay of those resources. Such methods are currently used in other fields, such as systemic functional linguistics (SFL) and multimodal ethnography, to understand the essence of meaning-making as revealed through embodied interactions. Adopting a broader research perspective in the context of CT, then, would help avoid reducing embodied cognition to the degree of one's physical movement and focus on the meaning behind that movement.

There is additional concern over operationalizing CT and developing a psychometric assessment that measures its underlying constructs. As noted earlier, epistemology plays a role in how CT is approached by scholars. From an embodied perspective, CT develops as a result of learners' unique interaction with the environment and each other. Assessing CT from this perspective should therefore be adaptive to the "looseness into the human-environment coupling" (Abrahamson & Abdu, 2020, p.16). This *looseness* refers to the idea of an agent's ever-changing goals as a response to the ongoing interaction with the system's surroundings. A body perceives the environment in the form of objects' affordances; something that I can grab, or eat, or throw, or sit upon" (Gibson, 1986; see Gallagher, 2014, p.10). What an object affords might vary as a response to organisms' momentarily goal. Depending on the organism's purpose, the same object could afford to grab, throw, and/or sit up. For the body, this results in intentionally picking up on the affordances to generate a goal-directed response to what is perceived from the environment (Chemero, 2011; Michaels & Palatinus, 2014).

In the context of CT, this *looseness* translates as perceiving new opportunities (in the form of affordances) for action, grounded in the learning environment. This attention to the act of perceiving, in turn, carries methodological implications. Any selected research approach needs to be flexible enough to comply with the dynamic nature of CT, which is constantly evolving and shaped by learners' perceived needs at a particular moment. Kopcha et al. (2020) explored the dynamic nature of CT using a social semiotic approach to multimodality. In particular, the authors focused on the ways that human-environment coupling impacted learners' reasoning when solving computational problems. This view underlines the "body's feedback-driven role" in cognition (Wilson & Foglia, 2011, p. 8). For example, the learners in Kopcha et al. (2020) re-organized their environment to reduce the amount of work needed to manage the cognitive demands of a task (i.e., epistemic actions) (Wilson, 2002). This re-organization was ongoing, and in response to the way that new problems and ideas emerged over time. In this way, the authors were able to capture the ways that the dynamic nature of CT. By using a supra-disciplinary approach such as a social semiotic perspective of multimodality, the authors were able study CT beyond the traditional view of CT as the sum of technical skills or a programming practice.

Computational Thinking and Information Processing

As argued above, most of the seminal scholars of CT (Papert, 1980; Perlis, 1960; Pôlya, 1945) had put an enormous effort to demarcate CT from programming/or algorithmic thinking. Overall, they described CT as a unique way of thinking that would end up with the development of higher-order thinking skills. There is growing evidence that supports those seminal works. That is, scholars today are arguing that CT should be treated as a unique form of thinking that aids problem-solving and it should be freed from the entrenched assumptions of information processing theory (Grover & Pea, 2013, 2018; Kopcha et al., 2020; Yaşar, 2018).

To date, most of the problems with the description and assessment of CT have risen due to its strong connotation of information processing theory and computational devices (Berland &

Wilensky, 2015; Yaşar, 2018). From the perspective of information processing, the brain works analogously to a computer; cognitive processes are explained through the manipulation of mental representations. The brain (i.e., a computer) creates an algorithm (mental representations) and practices that algorithm when solving problems (Mayer, 2003).

Accordingly, there have been numerous attempts to study CT through cognitive mechanisms such as mental schemas, information storage, and retrieval (Ambrosio et al., 2014; Yaşar, 2018). With each of these approaches, "mental processes are either identical with brain processes or exclusively realized by brain processes" (Rowlands, 2010, p. 2). Mapping human cognitive mechanisms in this way—that is, similar to the ways in which a computer works—is problematic from an embodied perspective because it largely ignores the role of the body and its interactions in computational processes. Incremental evidence points out how learners embodied interactions take part in understanding abstract concepts (Abrahamson & Lindgren, 2014; Hall & Nemirovsky, 2012). This notion runs parallel to the pedagogy of "*action-before-concept* learning" in which learners' sensorimotor interactions later inform the conceptual knowledge formation (Reinholz et al., 2010, p.1490). Likewise, Goodwin (2007) suggested that learning is the product of the "collaborative actions of multiple parties, and structure in the environment" (Goodwin, 2007). Overall, cognition rather arises in a framework in which "a brain in a body in an environment" in constant interaction and CT should be examined accordingly (Richardson & Chemero, 2017, p.39).

Computational Thinking as an Embodied Phenomenon

Up to this point, computational thinking has been presented a way of thinking that has far-reaching cognitive implications for teaching & learning when compared to the ways in which it has been conceptualized (e.g., information processing theory). For the purposes of this dissertation, and drawing on the literature review presented above, CT will be defined as an embodied phenomenon that is (i) a non-linear, dynamical system that (ii) is extended onto participant's bodies and environmental structures. As shown in Table 1, this definition is based upon the perspectives and concerns over CT in K-12 education present at this time. Table 2.2 contains a brief description of each perspective/concern, then presents the practical and methodological implications of each concern. For example, when CT is defined as a reactive cognitive process that draws on human perception, one practical implication is that the design of the learning environment should be flexible enough for learners to adapt to and make use of the various tools for supporting CT.

Table 2.2

Description and Characterization of CT from An Embodied Perspective

Theme	**Description**	**Implication**	**Methodology**
CT is an **embodied phenomenon**; it is extended onto the participant's bodies and environmental structures.	Any cognitive activity stretches beyond the boundaries of an organism (Favela & Chemero, 2016). Therefore, a complex system has multiple (i.e., homogeneous/heterogeneous) interacting components.	CT emerges and develops through interaction with the people and tools in the learning environment.	CT manifests through multiple modes in which learners co-construct meaning during embodied interaction: participants use of bodily resources, the objects, and the utterances constitute a “small ecology” (Goodwin, 2007, p.199).

CT develops in a **non-linear, and dynamical system**.	Feedback interactions within & across levels of the subcomponents identify a collective complex behavior, which displays a non-linear & unanticipated progression. 1. Positive feedback exchanged between the subsystems amplifies deviations. 2. Negative feedback exchanged between the subsystems mitigates deviations (Nathan & Swart, 2020).	CT develops in a complex system that involves agents' "brain in a body in an environment"(Richardson & Chemero, 2017, p.39). Feedback oriented interactions in the context of robotics therefore are grounded in the system's multiple interacting components: 1. Peer-to-peer multimodal interactions (e.g., discourse, gesture) 2. Peer-to-tool (e.g., robot) interaction	Cognitive processes should be evidenced holistically through learners' embodied interactions with technology (i.e., the robot), the environment, and each other.
CT is a reactive cognitive process that is **adaptive** to the environment.	1. Agents are learning from their interactions. 2. The goal of the agents change as a response to the ongoing interaction with the system's surroundings.	The shape and the direction of embodied interactions are determined by the current goal of the learner, which is not predictable but rather emergent.	"Looseness into the human-environment coupling" (Abrahamson & Abdu, 2020, p.7) is a design implication that highlights the adaptive nature of complex systems. Therefore, a multimodal transcript should be sensitive to how learners move across different modes.

In traditional cognitive science, cognition is associated with the brain, where cognitive activity is explained through the act of storing and manipulating mental representations (Mayer, 2003). Embodied perspectives confront the notion that the brain is solely responsible for cognition, and explore either the causal or constitutive role of body and environment in cognitive processes (Jacob, 2016; Favela & Chemero, 2016). In doing so, embodied cognition challenges the idea that the brain "presents and computes"(Branquinho, 2001, p. 15); rather cognition develops through the coupling of brain, body, and environment (Chemero, 2011; Gibson, 1977, 1979/1986; Goodwin, 2007; Merleau-Ponty, 1962/1965; Thelen & Smith, 1994).

Embodied cognition is not a new school of thought. Philosophy of mind has been discussing the connection between the mind and body for almost a hundred years, and through time, a variety of research domains such as robotics, neuroscience, phenomenology, cognitive psychology, learning sciences got involved with this overarching philosophical issue, and then addressed different research phenomena through the translation of its implications within and across these realms. However, theoretical connection between these different disciplines still lacks (Engel et al., 2015). Even though a few attempts have been made to create a unified cognitive theory, the literature has still fallen short of fully representing the scope of the relationship between the mind, body, and environment (Di Paolo & Thompson, 2014). This issue is due, in large part, to a lack of agreed-upon perspective in the literature about the scope of the phenomenon 'embodiment'.

A lack of agreed-upon perspective in the literature about the scope of embodiment is prevalent in education research. Some researchers have taken up embodiment as a state of being; for others, it focuses on the way action comes from the embodiment of abstract ideas and thinking (Hirose, 2002). Likewise, some have focused on the embodiment as physical manifestations through bodily modalities (Streeck et al., 2011). In contrast, others have focused more on embodiment as a socio-cultural phenomenon (Varela et al., 1991). This has resulted in multiple and, at times, divergent ideas about what embodied cognition is and how it might support learning and analysis in today's educational contexts.

Today, a broad spectrum of theories that involve research programs such as embodied cognition, embedded cognition, ecological psychology, and extended cognition keep informing educational theory (Gallagher, 2014; Hutto & Myin, 2017; Rowlands, 2010). In this dissertation, CT therefore will be studied as an embodied phenomenon – that is, as complex, dynamic cognitive activity that is extended to include participants' bodies and environmental structures. This definition draws on the integrity of the mind-body-world as a unit of analysis in a cycle of perception and action (Bullington, 2013; Richardson & Chemero, 2017).

Phenomenological Roots of Extended Cognition for CT

Most of the inherent controversies to the description and exploration of CT are due to CT being reduced to a programming practice, or viewing the brain as an information-processing unit. Such misconceptions still persist and undermine the significance of CT. As do many others, Shute et al. (2017) noted that there is a lack of in-depth exploration of how CT develops as a way of thinking in the current literature. In other words, there is a lack of research that addresses the underlying cognitive mechanisms of CT and its relationship to higher order thinking skills. As CT is at the intersection of learning sciences and computer literacy, these questions have rarely been addressed from the cognitive science perspective.

Tracing extended cognition back to its phenomenological roots offers insight into how CT develops in a framework in which "a brain in a body in an environment" constitutes a dynamical system in itself (Richardson & Chemero, 2017, p.39). Merleau-Ponty's (1945) phenomenological and philosophical account of human perception is considered the foundation of embodied cognitive science, with a particular focus on extended cognition. His work has led to the formation of cutting edge theories such as ecological psychology, situated robotics, among others that challenged the classical understanding of cognition that is sandwiched between perception and action. These theories mark the period as post-cognitivism in that the integrity of body and mind become central when studying cognitive processes.

Merleau-Ponty (1945) tried to understand the role of the body in cognitive processes. Building on the work of Husserl, Merleau-Ponty challenged the notion that the body is passive and peripheral to cognition. His proposal was in clear opposition to Descartes' mind and body separation, which holds that the body is simply an object that encircles the mind. For Merleau Ponty (1945/1962):

> The world is...the natural setting of, and field for, all my thoughts and all my explicit perceptions. Truth does not inhabit only the inner man, or more accurately, there is no inner man, man is in the world, and only in the world does he know himself. (p. xii).

This quote suggests how the body is integral to the way humans think, reason, act, and even exist in the world. Using the phrase, "being-in-the-world," Merleau-Ponty was suggesting that knowledge arises from our existence – that is, we come to understand the world and ourselves by "being in the world" (p. 84) rather than cognitive processing that resides solely in the brain. Merleau-Ponty's notions of being in the world sparked an interest in the exploration of the phenomenology of tool-use. Favela and Chemero (2016) draw on this notion to explain how "tools can be seamlessly integrated into one's experience of the world" (p.63). This part of Merleau Ponty's (1945) research particularly highlights the pliable nature of bodily boundaries; any cognitive activity stretches beyond the boundaries of an organism (Favela & Chemero, 2016). This experience is always embodied and helps expand embodied capacities as in the case of the blind man's cane extending his perception.

On the basis of the arguments above, Favela and Chemero (2016) called into question the notion that cognition resides in the brain alone: "if it is believed that cognition is embodied, that is, cognition is not confined to the brain, then should cognition also be treated as being limited to residing within the skin, scale, or feather boundaries of an organism? " (p.70). Following this inquiry, this dissertation focuses on exploring how CT extends beyond the brain and develops through interaction with the people and tools in the learning environment. This focus builds on a growing interest in understanding CT beyond a specific set of skills or outcomes (see Fadjo, 2012; Grover & Pea, 2013; Lu et al., 2011; Nemirovsky & Ferrara, 2008; Sung et al., 2017). It also conceptualizes CT as part of a dynamical system that is ever-changing; the components of that system (e.g., learner, tools, other people) both influence *and* are influenced by a learner's actions (Richardson & Chemero, 2014; Yaşar, 2018).

Dynamical Systems

For Nathan & Swart (2020, p.5), learning processes emerge in a complex system. Such systems have certain characteristic features, including "non-linearities of feedback" and "feedforward processes to self-regulate " (Nathan & Swart, 2020, p.6). Here, the authors are referring to the way that all complex systems feature adaptive behaviors in reaction to ongoing changes in the environment. Thus, non-linearity refers to the lack of a proportional relationship between cause and effect; in contrast, linear systems assume that any single step is always predictive of the next (Richardson & Chemero, 2014; You, 1993). A key shortcoming of the linear perspective is that it ignores the within- and across interactions in the various levels of a system, in which a small intervention in one subsystem can cause a disproportionate change in the overall system's behavior (i.e., butterfly effect) (You, 1993). Those within- and across-interactions, however, are important when CT is viewed as a complex, dynamic process because they refer to the emergent and unpredictable nature of that system (Richardson & Chemero, 2017). This means that isolating one component from the system's other components is not possible when identifying the exact cause of the system's behavior. Rather, those components work in synergy with one another – that is, they are self-organizing. These two characteristics of dynamical systems – self-organization and emergence – are essential to studying CT as a complex system.

Self-organization

Richardson and Chemero (2014) describe self-organization as "behavioral patterns that emerge from the interactions" (p.40). In other words, in self-organizing systems, overall behavior is coordinated through its parts' interactions, without the need of any central controlling unit. A murmuration behavior of a flock of starling can be given as an example. The behavioral patterns of starlings in a murmuration emerge as its members interact with each other. It is also coordinated based on feedback provided within and across its interacting components (Jacobson et al., 2016; Richardson & Chemero, 2014). Overall, a complex system self-organizes its behavior based on feedback-based interactions, which cannot be predicted by looking at the behavior of each individual part.

You (1993) provided insight into the ways that learning as a self-organizing system. For You (1993), the acquisition of new knowledge creates a cognitive conflict within the overall cognitive system. That conflict challenges one's existing knowledge, which then encourages learners to re-organize (i.e., self-organize) the system's components and adapt to new and emergent conditions. From an ecological perspective, this self-organization involves more than just the brain. When a body interacts with an object in the environment, it is perceiving the possibilities that the object offers. Action is taken based on what is viewed as possible, and how that action can help achieve the current goal. From this perspective, learning is viewed as "a fundamental reorganization of the system and its components rather than the mere addition of information" (see You, 1993, p. 24).

Similar to what You (1993) proposes, Jacobson et al. (2019) claimed that any learning theory should employ the fundamental concepts of complex dynamical systems theory, with a particular focus on emergent and transformative characteristics of human learning. According to Jacobson et al.'s (2019) complex system's conceptual framework for learning (CSCFL), learning is self-organizing because it is the result of (1) constant interactions of systems' components that operates within simple rules, and (2) feedback disseminated through different levels of a complex system. It can be inferred, then, that self-organizing behavior could be studied through the various interactions between the levels of a complex system.

Emergence

Emergence is a characteristic of complex, dynamical systems that is related to self-organization. In every complex system, an underlying, yet covert order operates (Agarwal & Prasad.1997). That order is often unpredictable, emerging in reaction to the various factors, both within and external to the system (You, 1993). Nathan and Swart (2020) describe emergent behaviors as those that cannot be anticipated based on the behaviors of its individual components. Thus, emergence refers to the way that a complex system can influence and change the environment which, in response, requires the system to *be influenced by* the environment (Hayles, 1990; Richardson & Chemero, 2014).

In the context of learning, emergence implies that learners engage in patterns that are unanticipated, and disordered (You, 1993). Jacobson et al. (2019) described how a learner's "aha moments" (p.113) help display the emergence of learners' conceptual change in the development of concept comprehension. In another example, the authors conceptualized emergence as the "collaborative interactions of students leading to convergence in problem solutions" (p.113). Overall, these authors and others (e.g., Kopcha et al., 2020) have noted how learners who engage in problem solving activity do so in an emergent manner, where each attempt at solving a problem leads to new conditions that the learner must react to.

CT As A Dynamical System

In the context of CT, a dynamical system perspective would mean that a variety of skills that are pertinent to CT (e.g., algorithmic thinking, debugging) emerge and develop in a context that has multiple interacting components. Current research supports this perspective, where CT has been found to develop through an emergent and self-organizing manner in which learners' bodily movements, use of tools, and embodied interactions are in constant interaction (Berland & Wilensky, 2015; Kopcha & Ocak, 2019). These multiple interacting components constitute a system that Goffman (1964, p.64) termed an *"ecological huddle"*—that is, a temporary coalition of people, organized around actions and, in turn, reactions that serve a common goal. The establishment of CT as a form of ecological huddle is significant because it suggests how CT can be viewed through a learners' embodied actions, such as their shared and goal-directed attention towards particular objects and incidents (see Streeck, Goodwin, & LeBaron, 2011). All these objects and incidents of mutual interest fall in the shared territory of an animal-environment system in which learners' cognitive activity is extended. This aligns with the notion of how recent literature on CT suggests that the social, verbal, and non-verbal aspects of human interaction that occur as participants come together within a given space to solve problems or take action (Melcer & Isbister, 2016; Sung et al., 2017).

Based on the argument above, CT draws upon multi-semiotic resources (e.g., learners' discourse, gesture, tools) during solving complex-problems. Those components are naturally self-organizing, which means that a central unit does not control the behavior of the overall system; rather, the system organizes itself as a result of feedback disseminated through the interactions of the systems' subcomponents (Jacobson et al., 2016; Richardson & Chemero, 2014). For example, Richardson and Chemero (2014) give the example of nest-building ants, murmuration behavior of starling flockings in which collective social action results from individual and higher-level interactions in a system. In another example, Hutchins and Nomura (2011) claim that "one speaker begins an utterance in a way that projects possible completions, another speaker then contributes utterance elements that are incorporated into a jointly produced utterance" (p. 29).

In the context of CT, self-organization can be seen in the way that learners coordinate their activity with the purpose of "achieving the more immediate goal of guiding behavior in response to the system's changing surroundings" (p. 4). Therefore, the shape and direction of this interaction is determined by the current goal of learners that is updated through "feedback interactions" (Jacobson et al., 2016, p.211). For example, Kopcha and Ocak (2019) studied how momentary feedback received from the robot as it navigates across a 3'x 3' grid of obstacles helps participants conceptualize and simulate the robot's next movement. In other words, "the temporal and sequential organization" of learners' embodied actions (Knoblauch et al., 2009, p. 19) heavily draws on the feedback loop grounded in the tools, environmental structures, and reciprocal dialogue.

In the preceding and current literature, there is a growing push-back against conflating CT with activities such as algorithmic thinking, programming, and design thinking. This push-back can be traced to Perlis (1960) and, later, Papert (1980). According to recent research trends, CT rather is a cognitive process that could be strengthened via developing learners' perceptual and embodied reasoning (see Kopcha et al., 2020; Reinholz et al., 2010). For example, Kopcha et al. (2020) found that children conceptualized one-length in relation to the other to successfully move the robot to the target location in the right amount of time. This involved tailoring the original mathematical units to the programming dynamics while preserving the constants. This type of exploration is grounded in learners' bodily interactions with and through the systems' surroundings. Abrahamson and Lindgren (2014) explained this design principle as *dynamical conversation*, in which "the learner needs to discover an action pattern (law of progression) that maintains constant a property of the system" (p.8). Computational thinking, therefore, extends beyond learners' bodies to encapsulate human-environment interaction, by drawing on the principle of dynamical conversation in computational thinking (Abrahamson & Lindgren, 2014; Favela & Chemero (2016).

Methodological Approaches for the Study of CT as a Dynamical System

If CT is viewed as a dynamical system, then the question that arises from this perspective is: *How can researchers study CT in a way that upholds the complexity of the system?* As noted in the introduction, CT is more often assessed through standardized and/or multiple-choice tests that focus on achieving a specific skill (Atmatzidou & Demetriadis, 2016; Bers et al., 2014; Román-González, 2015). When CT is viewed as a dynamical system, however, such methods fall short because they assume that CT is a linear process — that is, that one specific *input* into the system will, in turn, lead to a predictable *output* from the system. From a dynamic perspective, this fails to capture the emergent and self-organizing nature of CT as a non-linear process. From a dynamical perspective, insight into the nature of CT would come more from *the* *way in which the components in the system interact with each other,* and how this interaction shifts *over time.* For example, Jacobson et al. (2019) authors suggested that self-organization could be studied through the *"*(a) interactions of individual agents or components of the system that often may be described in terms of simple rules; (b) feedback interactions between agents that may occur within or across system levels" (Jacobson et al., 2019, p. 113). Whereas the emergence aspect suggests that overall learning behavior that cannot be anticipated based on the behaviors of its components due to non-linear development patterns (Nathan & Swart, 2020). This, therefore, requires moving away from linear causality and embracing a more comprehensive understanding of the organization of a system shifts over time to reveal the aspect of emergence.

A social semiotic approach of multimodality is strongly aligned with studying cognition and learning as a dynamic meaning-making activity through human interaction (see Table 2.3). One reason is that social semiotic perspective explores different modes of interaction (e.g., discourse, writing) available to an agent for self-expression, seeking to identify what a mode affords in a particular social context and how an individual chooses one mode over another (Jewitt et al., 2016). SS particularly focuses on the meaning that a mode encapsulates, and how this meaning shifts over time. From the perspective of SS, the notion of mode is at the forefront, and modes are seen as tools for meaning-making. A mode is briefly described as a set of semiotic assets that are used by the speakers for meaning-making. To validate a semiotic resource as a mode, speakers need to act on these resources meaningfully; a higher frequency of emergence of the modes of interaction might be seen as an indicator of purposeful action. These modes might have varying forms and organizing structures such as image, writing, gaze, discourse, etc. Each form affords a particular function while making a dialogue with its semiotic content. For example, the order of objects, as organized in an image, implies particular meaning for the analysis (i.e., compositional function). In contrast, for textual data, grammatical and lexical preferences do imply meaning (Fitzgerald & Young, 2006). Overall, these affordances are not set-in-stone, rather socially-constructed, and therefore sensitive to the social context they are produced in (Jewitt et al., 2016).

Table 2.3

Major Principles of Multimodal Transcription from A Social Semiotic Perspective

Theoretical / Epistemological Function of a Transcript	Explanation
1. Multimodal transcription is "not only the transcription of speech" (Bezemer, 2014, p.193).	Multimodality refers to data that is not necessarily made up out of one mode of communication (e.g., linguistic, numerical). Meaning-making resources (a.k.a., modes) carry both verbal and non-verbal aspects that provide insight into one's thinking. Social semiotics researchers analyze data sources that are produced in the natural flow of life, such as in-situ artifacts (e.g., children's drawings) (Jewitt et el., 2016).
2. Transcripts serve as "empirical material through which transcription as a social, meaning-making practice (and changes therein) can be reconstructed" (Bezemer, 2014, p.193).	From a social semiotic perspective, a transcript does not serve as a verbatim report of the dialogue, but an epistemic practice that gives agency to the transcribers to reconstruct the data while addressing the research questions (Bezemer & Mavers, 2011). The process is known as "re-making of observed activities in a transcript that can lead to fresh insights" (p.196).
3. A social semiotic approach explores "the potentials and constraints of modes of transcription" (Bezemer, 2014, p.193).	Social semiotics explores the meaning that a mode conveys, and how this meaning shifts over time.

4. A social semiotic approach addresses "changes in the multimodal landscape of representation and communication" (Bezemer, 2014, p.193).	Multimodal transcriptions are “transducted and edited representations through which analytical insights can be gained, and certain details are lost” (Bezemer & Mavers, 2011, p. 196). Therefore, the merit and/or accuracy of transcripts is not determined by how they are the replica of the audio and/or video footage; instead how efficient they are addressing the research questions from the researchers’ theoretical perspective.

For Bezemer and Jewitt (2010), a mode is characterized by social or cultural norms inherited from a community. For example, the very same gesture might transmit different meanings in the context of sports than education (Bezemer & Jewitt, 2010). This characterization is an ongoing process because the social dynamics of a particular context is shaped as a result of constant interaction among interrelated components in a system. In terms of this perspective, the meaning that a mode conveys shifts over time, as the participants act upon them. This aligns with the notion of how meaning does not develop in vacuum; rather it is constructed by the participants, who are “remaking meaning and choosing the most apt signifier to represent the meaning signified” (Dicks et al., 2011, p.229). This dynamicity complies with the central tenets of both social semiotics and embodied cognition. From both perspectives, signs that are used to produce meaning are neither pre-given nor abstract; rather the sign making is a social activity and gains meaning in terms of the context and culture as people engage in (Jewitt et al., 2016).

Within the social semiotic approach to multimodality lie multiple approaches to the analysis of data, each of which draw on social semiotics while also aligning with the perspective of dynamical systems. One such approach is the grounded approach. The grounded approach is a qualitative research method that enables the application of near-decomposition to the analysis of qualitative data while studying a complex dynamical learning phenomenon.

Near-decomposition

To study complex dynamical systems, Nathan and Swart (2020) suggest functional decomposition as an efficient strategy to deal with the complexity that manifests itself either in the phase of theorization and/or implementation; or assessment. The authors describe near decomposition as breaking-down a complex system into its functional parts to isolate and fix the flawed sub-system(s) separately from the whole. For Nathan and Swart (2020) functional decomposition, therefore, offers an initial, pragmatic approach to deal with the complexity that might arise from learning design, implementation, and assessment.

Near-decomposition is a pragmatic strategy for a couple of reasons. One benefit is that it enables researchers to near-decompose the overall system even though the isolation of subsystems is not possible due to interdependent interactions within and across the systems' elements. Examination of the within system interactions, therefore, requires a naturalistic and phenomenological understanding to make an educated guess on what part needs to be at the core of the study. The grounded approach and near-decomposition are compatible because the grounded approach enables to near-decompose overall system around the core variable and identify the interconnected subsystems. In qualitative research, therefore grounded approach is a useful method for guiding researchers where to start in analyzing and assessing their data.

It is important not to confuse functional decomposition with linear methodological approaches. Conversely, functional decomposition accepts the fact that cause and effect have a disproportionate relationship; a small change in a subsystem can have a much larger impact on the larger level due to interdependent interactions. The major characteristic feature of nearly decomposable systems is that the within subsystem interactions are comparably stronger than the across subsystem interactions. The weaker interactions across the subsystems, therefore, enable researchers to isolate a subsystem and study it. For example, Nathan and Swart (2020) give an example from the Wright brothers approach to design a plane in which the functional decomposition involved the “wings that produce lift, propellers that produce thrust” (p.17). Wings and propellers, therefore, were identified as the subsystems, to be studied and optimized in isolation (i.e., design-wise), and then to be assembled back together. Nathan and Swart (2020) frame this as the combination of scale-down (i.e., micro-level) and scale-up (i.e., macro-level) approaches to study complex systems; scale down is for isolating the parts for the corrections and then scale up to integrate the subsystems back. Similarly, the combination of grounded approach and transduction offers an efficient framework to study CT as a complex system.

Grounded Approach

The grounded approach is a powerful, systematic approach that allows researchers to decompose the overall system into its functional parts when dealing with large volumes of complex data; it is particularly helpful if a researcher does not know where to begin data analysis prior to generating a theory. While there are several techniques associated with the application of grounded theory approach, embedding near-decomposition points at distinct steps to follow, such as “inductive analysis in which categories are generated from data, identification of a core category, and ongoing memo writing” (see Levy, 2015, p.75). The grounded approach techniques, such as the assignment of a core variable (i.e., the central mode of interaction) and its interconnected categories, help identify the near-decomposable part of interaction dominant, complex systems.

The overarching purpose of a grounded approach is to generate a theoretical understanding about the subject of the study (Glaser & Strauss, 1967). When constructing theories; a grounded approach provides certain advantages by engaging researchers in systematic coding processes. First of all, these processes are often inductive, giving researchers enough flexibility to make adaptations to their research questions as they continue conducting data analysis (Johnson & Parry, 2016). This is also known as simultaneous data collection and analysis in which one process is not a precursor to another; rather iterative (Carmichael & Cunningham, 2017). The nature of grounded theory as a methodology is therefore much aligned with dynamical systems. First of all, linear models for research are characterized by strict procedures in which jumping into a second step is not likely without completing the first (You, 1993). A grounded theory, on the other hand, allows researchers to adjust their approaches to data collection as they analyze it; it is a methodological approach that is adaptive to the emergent findings where these findings bear a potential for changing the rising theory on the spot. Second, a grounded theory enables researchers to work in the flexible boundaries of a learning phenomenon as it points out new directions at the time that the analysis continues. Every emergent category configures the emergent theory either by opening up new horizons or strengthening prior findings.

Transduction

Another such approach is a process called *transduction.* A process of transduction is a significant process of a social semiotic approach to multimodality for a number of reasons. First of all, transduction is the translation of modes (e.g., gaze, gestures, utterance) into a written account (Jewitt et al., 2016). Jewitt et al. (2016) explain that the process is always transformative when the meaning from one mode is carried over to the other. The account of transduction fundamentally lands on the interpretive lens of the researcher; the story of the data tells (e.g., video) is written to develop insights for the research questions. Bezemer and Mavers (2011) underline the significance of the process with the claim of how a multimodal transcription of video data is “transducted and edited representations which analytical insights can be gained and certain details are lost” (p. 196). It is the researcher’s voice that shapes the transduction practices; namely their epistemic and representational choices. Different stylistic representations have impact on framing moving-across the modes (i.e., transduction). For example, “a sequence of stills can be shown to mark the moment-by-moment shifts in unfolding interaction, and different moments in time can be joined together in one image” (Jewitt et al. 2016, p.148).This transitioning could be indicated through using a certain type of punctuation, transcription conventions (Bezemer & Mavers, 2011; Cowan, 2014; Mondada, 2018).

Transduction is a powerful analytical technique to attend self-organizing and emergent nature of CT as a complex, dynamical system. From the dynamical systems perspective, transduction plays its part to designate and/or interpret interdependent interactions from one mode to another (see Iedema, 2003). Shifting from one mode to another—from talking to coding (i.e., from working at the grid to the computer)—can be viewed as a form of resemiotization, where every act of resemiotization operates within a certain logic (Iedema, 2003). This logic informs moving across modes and leads to reorganization of meaning-making resources, namely spatial and temporal organization of the behavior during social interaction. Therefore, researchers can study dynamical systems by understanding the reasoning behind the shifts across modes.

Moreover, Goffman’s (1974) frame analysis—the one inspired by Western dramaturgy—suggests that some modes mark the beginning and end of a frame. For example, rising curtains, gradually fading lights give a cue to the audience indicating that the performance is about to begin. As is the case with reciprocal dialogue, modes such as “mutual orientation of the participants” could mark the beginning and the end of a frame (Streek et al., 2011, p. 2). Even the slightest changes made to the displays of mutual orientation provide evidence of learners' self-organizing of semiotic resources in a response to changing environmental conditions. Goffman's perspective informs transduction in that transduction aims to reveal the meaning behind and complexity within social interaction through the display of spatial and temporal organization of the behavior.

Transduction also provides certain advantages that reveal the emergent nature of dynamical complex systems. Bezemer and Mavers (2011) argued that a multimodal transcripts "are not merely descriptive, nor are they mere *translations*" (p.196), but rather a process of re-construction of evidence that is majorly informed by the researcher's interpretation of the phenomenon. Transduction reflects this process. Typically, the product of transduction is a coherent story, told from researcher's perspective, of how people attend to multiple meaning-making resources simultaneously. This helps preserve the temporal organization of the modes while developing intuition for the emergent reasoning patterns (i.e., the underlying logic). The format of the transcript and transcription conventions (e.g., font-style, use of brackets) aid this process in that they help better communicate the self-organizing nature—that is, the spatial and temporal organization of various modes—in a multimodal transcript.

CHAPTER 3

Methodology

This dissertation is part of a design research project that focused on developing and validating a STEM-integrated robotics unit in elementary school classrooms in the United States. The unit, called *Danger Zone* (Choi et al., 2015), was implemented in a 5th grade classroom as part of the regular science curriculum. The STEM-integrated robotics unit involves six consecutive lessons, each of which lasted approximately 50 minutes. The curriculum was designed to help participants explore science, technology, engineering, and mathematics concepts through robotics by the rules set in the pre-configured science scenario. Data collected on the final implementation of *Danger Zone* suggested that the unit was engaging to the participants; the teachers, in particular, noted how the unit supported mathematical and scientific reasoning as part of a larger problem solving process (Kopcha et al., 2017).

For the current study, the primary focus was on revealing the ways that the participant's computational thinking (CT) emerged as an embodied phenomenon. The primary source of data was a 100-minute video collected from a rural school in the Southeastern US in which two 5th grade participants engaged in *Danger Zone* (Choi et al., 2015) as part of their science class. The video data, which was collected as part of the larger design research project described above, was analyzed in three different ways: (1) a grounded approach to analyzing the multimodal transcript, (2) a process of transduction with a priori coding and thematic analysis, and (3) an artificial-intelligence-enhanced (AI-E) pattern recognition approach that uses cloud-based machine learning technology to analyze video data. The overarching methodological framework that guided all three analytical approaches drew on a social semiotic approach to multimodality. As explained in the literature review (Chapter 2), multimodal approaches are well-suited for the analysis of video data in that they deal with data that is not necessarily made up out of a single mode of communication (e.g., linguistic, numerical) but rather multiple modes that often take place simultaneously (e.g., talking while gesturing; moving one's body while using objects in the environment).

Research Design

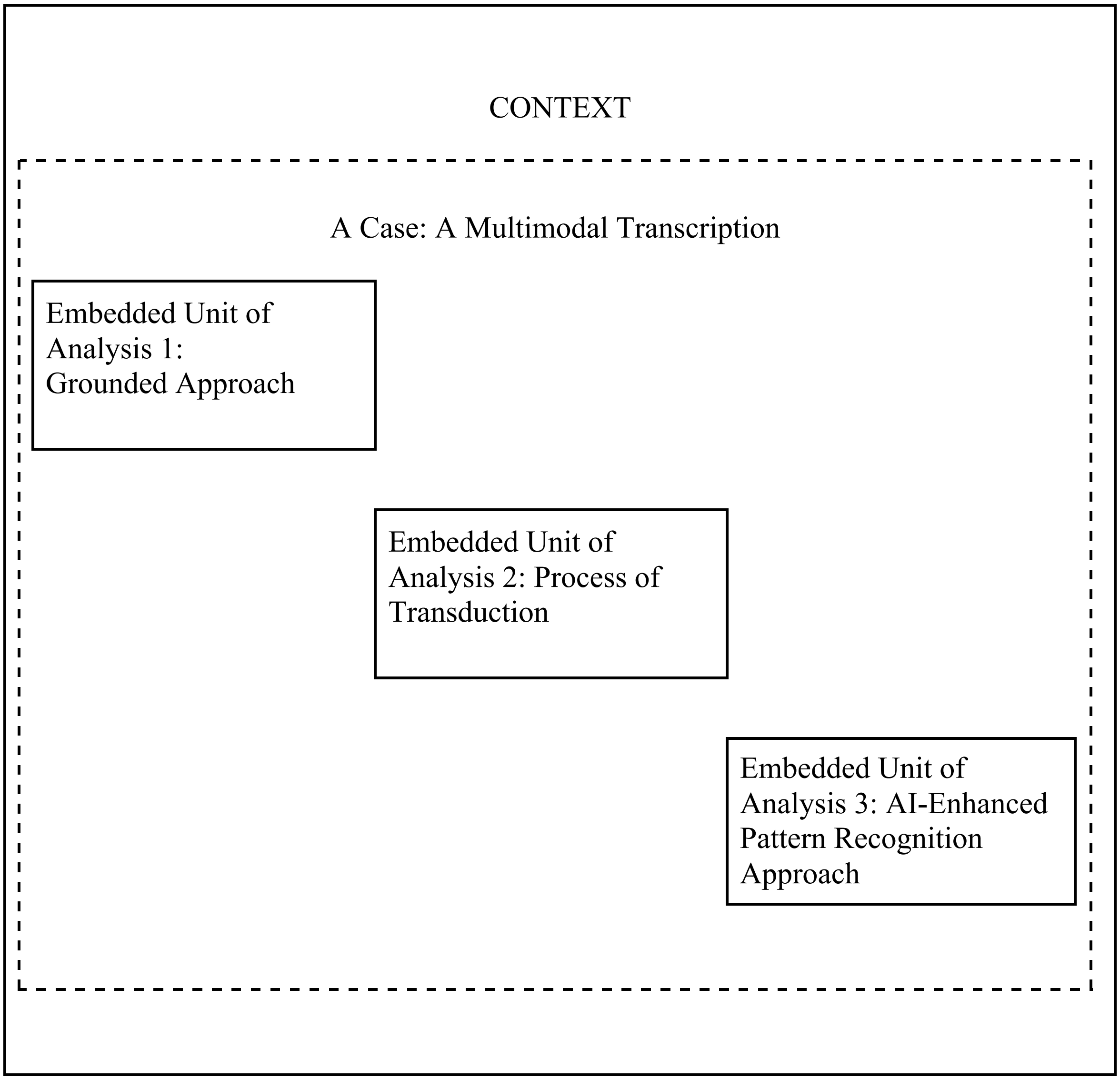
The research was conceptualized as a single holistic case study (Yin, 2012) that explored three different approaches to the analysis of children's CT from a social semiotic perspective of multimodality. The three different approaches were considered embedded units in that they each helped explore the overall case in a unique way. As shown in Figure 3.1, the ultimate goal of the case study was to look within and across the embedded units to identify the strengths and weaknesses associated with each. Using the lens of dynamical systems theory, each unit was examined for the ways that it addressed CT as emergent and self-organizing.

For Yin (2012), the purpose of a holistic case study is to draw a complementary picture of the research phenomena, where the layers of that picture are complementary. The dotted lines shown in Figure 3.1 reflect this complementiarity, suggesting that the distinction between the case and context is blurred. Because the case is the actual unit of analysis, this lack of distinction is embraced – the aim is to fully understand the phenomenon rather than focus on the generalizability of the findings. Yin (2012) explained that a case in a case study corresponds to a unit of analysis. Identifying a unit of analysis is not easy; rather, it is an iterative process that bears the potential for changing during data analysis. A single-case research design can have embedded sub-units to itself, aka embedded subcases. Any case study, then, could use distinct analytical methods for data analysis in a broad range of both qualitative and quantitative approaches or mixed (DeCuir-Gunby & Schutz, 2016; Runeson & Höst, 2009).

Above all, Ayres et al. (2003) highlighted the significance of adopting interpretive techniques to "provide a wealth of contextual richness and person-specific information without which that case cannot be understood" (p. 873). Because this research already uses a social semiotic perspective of multimodality, the analysis takes an interpretive view. Additionally, the embedded subunits (i.e., the different analytical techniques) provided a particular lens for analyzing and interpreting the data. The consecutive application of three analytical methods resulted in ongoing updates to and understanding of our initial transcript that revealed the strengths and weaknesses associated with different approaches to CT analysis.

Figure 3.1

Research Design: Embedded Sub-cases Within an Overall Holistic Case



Note. Adapted from Yin (2012).

To date, the results of (1) the grounded approach and (2) the process of transduction have been published through a process of peer review (see, respectively: Kopcha & Ocak, 2019; Kopcha et al., 2020). This study draws on those prior findings while also going beyond them in two distinct ways. First, this study includes a third analytical approach that uses artificial intelligence to enhance pattern recognition using the same video data. Second, the study treats each approach as a unique unit of a larger case that can be analyzed by looking across units using criterion related to dynamical systems (i.e., emergence and self-organization). By comparing three different methods of analysis that align with a single overarching methodological framework, this study addresses the lack of robust tools and methods for studying CT as an embodied phenomenon. Of particular interest is how each approach reveals the ways that learning in the context of CT emerges and develops as a complex, interaction-dominant process that is revealed through interaction with the people and tools in the environment.

A Social Semiotic Approach to Multimodal Transcription and Analysis

To that end, this section is devoted to explaining how the social semiotic approach to multimodality was used as a tool for analysis in the specific context of this study. It is organized in a way that reflects the background of the study and the major steps in completing the study. Those steps are presented in Table 3.1 and described in detail, below.

Table 3.1

Summary of the Steps to Multimodal Transcription

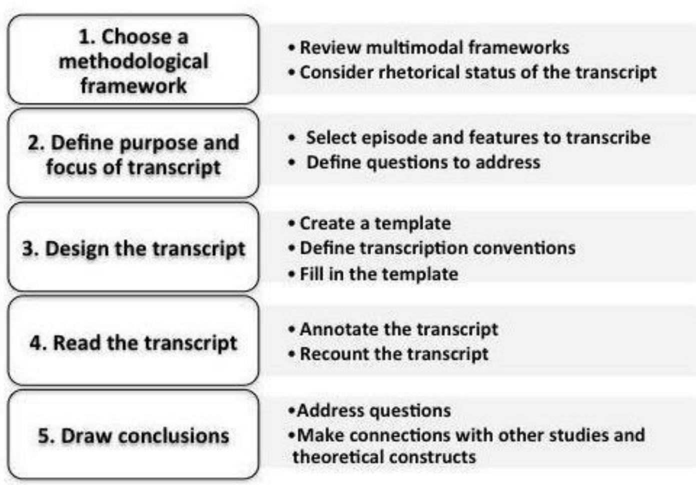
Major Steps in Completing the Study	**Select Approach for the Major Steps**	**Function of the Select Approach**
STEP 1: Choosing A Methodological Framework	Social Semiotic Approach (SS)	SS informs the rhetorical function of the transcript.
STEP 2: Creating A Multimodal Transcription As A Tool for Video Analysis	Social Semiotic Approach (SS) to Multimodal Transcription for the Analysis of Video Excerpt	SS informs the design of the transcript in terms of: 1. Transcription Conventions 2. Format 3. Transduction

STEP 4: Analyzing the Transcript Through Three Different Approaches	3.4.1 Coding for CT 3.4.2 Thematic Analysis of Embodied Interaction 3.4.3 AI-Enhanced Pattern Recognition Tool	SS informs embodied interaction analysis.
STEP 5: Conducting A Cross-Unit Analysis	Compare & Contrast Approach: A Cross-Unit Analysis To Provide A Holistic Picture of the Research Phenomenon	SS manifests itself through a variety of research methods in assessing multimodal data.

In this study, the multimodal transcript was developed using Bezemer's (2014, p. 156) five steps to multimodal transcription. The five steps and their sub-components are displayed in Figure 3.2.

Figure 3.2

Bezemer's Five Steps to Transcribing Multimodal Interaction



Step 1: Choose a Methodological Framework

For Bezemer (2014), the first step to creating a multimodal transcript is to select a proper methodological framework that aligns with researchers' purposes. This study uses a social semiotic perspective as the primary methodological framework (see Literature Review, Chapter 2, for more on this perspective). Creating a multimodal transcript from a social semiotic perspective has distinct theoretical and epistemological functions that a researcher needs to consider. Bezemer (2014, p.193) summarizes these as follows (see Table 3.2): (1) multimodal transcription goes beyond spoken words; (2) transcripts are a reconstruction of real events that (3) explore the meaning behind one's interactions; and (4) efficiently and effectively address the driving research question(s).

Step 2: Purpose and Focus

Creating a multimodal transcript is a significant practice that gives agency to the transcribers to reconstruct the data while addressing specific research questions (Bezemer & Mavers, 2011). The overarching question driving this study was: *How can embodied perspectives be leveraged into a research methodology in the area of children's CT?*

This was answered through a series of sub-questions:

1. How does a grounded approach to analyzing a multimodal transcript approach the study of children's CT as an emergent and self-organizing phenomenon?
2. How does a process of transduction with a priori coding and thematic analysis approach the study of children's CT as an emergent and self-organizing phenomenon?
3. How does an AI-enhanced pattern recognition approach approach the study of children's CT as an emergent and self-organizing phenomenon?
4. What are the key strengths and differences associated with the three different approaches to the multimodal analysis of children's CT?

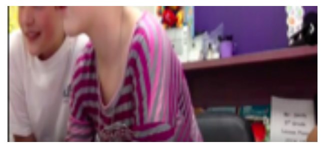
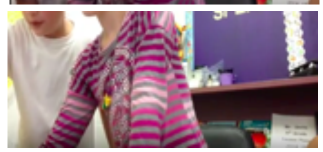
Step 3: Design the Transcript

Bezemer's (2014) ***third step*** to multimodal transcription suggests that the design of a transcript (e.g., layout, conventions) is crucial because it displays how different modes function all at once throughout the transcript (see Helm & Dooly, 2017). From the social semiotics perspective, meaning is communicated through the modes and shifts across the modes during social interaction (Bezemer & Mavers, 2011). In this study, a side-by-side display format was chosen to disclose the shifts in meaning across different modes in the transcript. The dialogue, which represents one mode, was presented in the first column as a verbatim transcription of the participants' discourse. This was coupled with images of the corresponding embodied interactions (e.g., gestures) that accompanied the discourse in the second column.

Stylistic conventions were employed to direct attention to the shifts in modes. The primary convention was the use of brackets, which contained a description of the interaction between modes in a given moment (e.g., [points at collection point on a piece of paper]). In addition, each image was labeled using a letter of the alphabet so that the temporality of the verbal and non-verbal modes was preserved. This was accomplished by adding to the dialogue the corresponding image label, set apart with a number sign (e.g., #a). Table 3.2 presents an excerpt from the multimodal transcript created as part of this study. As shown in Table 3.2, organizing the dialogue and images in a side-by-side fashion helped to preserve the temporal and sequential aspects of participants' embodied interactions.

Table 3.2

Side-by-side Organization of the Dialogue, Embodied Interactions, and Description of Activity

Utterances/Dialogue	**Embodied Interaction**	**CT / Description**
B: So, that means, right forward (#a), left backward [eyes are fixed upwards] G: Right forward [both lean towards the computer] ... B: You have to go first [points at the specific command on the screen] (#b). G: Yes, I do. Right! B: Those are going to go forward. Make that one go backward [points at the screen] (#c).	a.  b.  c. 	The boy debugs a failed turn; he displays gestures to indicate the wheel movement.

Step 4: Read (and Analyze) the Transcript

A social semiotic approach to multimodality is particularly useful to unfold the meaning that develops through different modes (e.g., speech, gaze, gesture) and artifact in a particular social context (i.e., robotics). However, it is important to note that, "transcripts don't speak for themselves" (Bezemer, 2014, p.163). Thus, Bezemer's ***fourth step*** entails reading through the transcript and analyzing the data to answer the driving research question(s). This is often accomplished through the fine-grained analysis of modes that are present in the multimodal transcript.

In this study, three different approaches were employed to support the fine-grained analysis of the same multimodal transcript: (1) a grounded approach, (2) a process of transduction with a priori coding and thematic analysis, and (3) an artificial intelligence (AI) pattern recognition approach. As shown in Table 3.3, each of these three approaches differs in terms of the aims and purpose of analysis. At the same time, each uses the broad methodological framework of social semiotics and multimodality to reveal how CT develops for young children as a result of their embodied interactions with each other and the environment.

Table 3.3

Emergent Themes and Categories From Three Different Approaches

Analytical Approach	**Description**	**Major Findings from Each Approach**
Grounded Approach	The purpose was to generate a theoretical understanding of children's embodiment of computational thinking during robotics activity, based on video data. The modes of interaction are examined separately.	We identified tool use as the core variable. The tools included basic unit movements, gestures, and the interactions with the robot, map, and the computer (Kopcha & Ocak, 2019).
Transduction	The purpose was to identify and describe the underlying mechanism of how CT emerges and develops through interaction with the people and tools in the learning environment. This goes beyond identifying a core variable; the goal was to interpret meaning making across modes (i.e., as a whole).	Multiplicative reasoning emerged as a guiding concept that remained central to participant's interactions with their environment (Kopcha et al., 2020).
AI-enhanced Pattern Recognition Approach	The purpose was to support multimodal data analysis by evaluating large data sets to help identify images of interest, patterns of interaction, and the possible meanings behind those interactions.	AI-enhanced served as proof of evidence to triangulate the findings from the human analysis.

Grounded Approach. The purpose of adopting a grounded approach was to generate a theoretical understanding of young children's embodiment of computational thinking during robotics activity. The techniques employed as part of the grounded approach included (1) an inductive process of narrowing down the phenomenon of interest, (2) open coding to identify core variables and themes, and (3) refining core variables and themes. The analysis and findings associated with the grounded approach, which also appear in Kopcha and Ocak (2019), are presented in this study in summary form for the ultimate purpose of comparison across analytical methods.

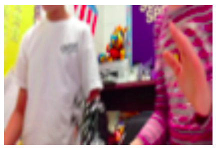
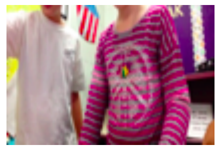
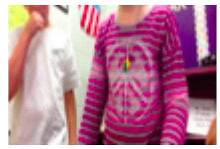
As presented in Kopcha and Ocak (2019), the grounded approach began with an inductive process to gain a preliminary understanding of participants' embodiment of robotics. The researchers read the transcript with the goal of narrowing down the research phenomenon. The phenomenon that the researchers identified focused on the ways that the participants' cognitive activity extended over the environmental structures during the robotics task.

With the research phenomenon broadly identified, data analysis started with open coding in which the researchers began applying codes in ways that made intuitive sense to them (Johnson & Parry, 2016). Our major goal was to "stay close to the data" (Charmaz, 2006, p.49) and identify recursive patterns in the data. This process resulted in the highlighting of the specific modes of meaning-making involved during the participant's computational thinking (1) tools/affordances, (2) gestures, and semantics/verbal content (3).

In the next phase, our research team came together in weekly meetings to develop initial themes and categories. To accomplish this, the researchers began to isolate and examine the different modes of interaction involved in the participant's interactions—that is, they analyzed the verbatim transcription of the speech and short sequences of images separately. This resulted in a prevailing theme: the children's computational thinking was supported by the tools that were employed during problem solving (e.g., gestures, robots). The analysis of short sequences of images also led us to observe how those "tools can be seamlessly integrated into one's experience of the world" (see Favela & Chemero, 2016, p. 63). Thus, the core variable associated with this study was the participant's tool use. Figure 3.3 displays the images associated with the participant's seamless use of the robot as a tool that supported their reasoning.

Figure 3.3

Tools Employed During Problem-Solving

a.  b.  c.  d. 

The final step was to engage in selective coding to derive further and refine the initial themes and categories around the core variable (Johnson & Parry, 2016). The refinement process was one of consensus building among the researchers. Consensus building is a process in which the researchers repeatedly meet to identify themes after independently applying those themes to the data (Tracy, 2010). In this study, it took the researchers three cycles of meeting after independent work to refine the themes and categories associated with the core variable. Those themes and categories reflected the participant's primary tool use (e.g., gestures, the map and the computer).

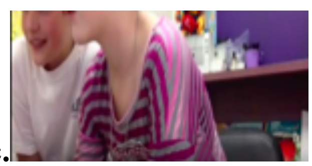
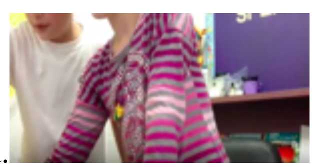
Transduction. To better understand the underlying mechanism of how CT emerges as an embodied phenomenon, the multimodal transcript was also analyzed through a process of transduction. As described in the Literature Review, Chapter 2, transduction is a common practice in the analysis of multimodal transcription from a social semiotic perspective. Rather than examine each mode in isolation, the goal is to make sense of participant's interactions across different modes; meaning is revealed through the various shifts in modes (Bezemer & Mavers, 2011; Bezemer, 2014). This approach to the analysis of multimodal transcripts focuses on generating a written account of the researcher's perspective. The written account focuses on emergent patterns and staying "close to the data" (Charmaz, 2006, p.49) to develop a holistic account of the participant's embodiment of CT. The analysis and findings associated with the transduction process, which also appear in Kopcha et al. (2020), are presented in this study in summary form for the ultimate purpose of comparison across analytical methods.

Initial Transduction. The transduction process began by first exploring the complementarity of different modes. Rather than examining each modality in isolation from other modes (e.g., grounded approach), the goal was to look across the images and matching discourse extracted from the video data to gain an overall sense of what was happening across modes over time. This was an ongoing and recursive process that continued until the transduction account was able to tell a coherent story of the participant's choice of modes and interactions at different points in time. Throughout this process, the researcher jotted down the thoughts, notes, and reactions to the data as suggested by Merriam (2009, p.178). This helped develop the transduction process while addressing the research questions.

Coding and Initial Themes. The next step was to conduct a read through the initial transduction and engage in coding. The goal was to begin to form an understanding of the overall patterns that were emerging and develop a stronger sense of what was happening in the data. To achieve this, codes were developed a priori. Drawing on Grover and Pea (2018), decomposition was defined as breaking a larger task into smaller goals; in the transcript, this code was applied whenever participants discussed the sub-steps associated with their overall goal (see examples in Table 3.4). Algorithmic thinking was characterized by precise, step-by-step calculations to solve the task, whereas pattern recognition involves recognizing similarities from previous experiences. These two codes were applied whenever the participants used precise mathematical computations as part of their thinking (algorithmic thinking) or drew on prior experiences with the robot (pattern recognition). Testing was about detecting and fixing an error in a solution to efficiently solve a problem. Testing was applied whenever participants found an error in the code.

Table 3.4

Initial Transduction Highlighting The Coding Scheme for Computational Thinking

Dialogue	**Gesture**	**Transduction**
G: Okay! Now we need a turn. B: Yeah! Now a turn to do that. G: Hold on! [leans forward] B: So, that means, right forward (**#a**), left backward [eyes are fixed upwards] (**#b**). G: Right forward... [both lean towards the computer] B: You have to go first [points at the specific command on the screen] (**#c**). G: Yes, I do. Right! B: Those are going forward. Make that one go backward [points at the screen] #d. G: Yeah! B: The speed is 0.4? G: Yeah, four for 0.4 [still looks at the screen].	a.  b.  c.  d. 	The pair returns from testing to continue decomposing the larger task. Both focus on turning left. The boy *moves his hands to show a turn* where the right wheel moves forward, and the left wheel moves backward. (# a-b) The boy's *eye fixes upward*, suggesting he is predicting the robot's movement. The pair then *focuses on the computer screen*, using algorithmic thinking to negotiate the speed and the movement of each wheel to arrive. (# c-d).

This process led to the development of several new codes. These codes addressed the interaction across modes and looking at how those modes interacted. For example, mathematical reasoning emerged through the participant's gestures and in conjunction with decomposition and algorithmic thinking. This happened as the participants interacted with the robot and other structures in the environment to break larger distances into unit squares.

Refine the Transduction Column And Thematic Analysis. Next, a broader level thematic analysis was conducted to determine the why and how details to explore the bigger picture behind the initial emergent patterns. The analysis focused on the parts of the multimodal transcript that were most relevant to the overarching research question—that is, to the development of young participants' computational thinking during robotics activity For example, one prominent pattern revealed the participant's embodied mathematical concepts as part of their computational thinking. The segments of transcript containing those patterns were then analyzed to establish a holistic understanding of the participant's mathematical reasoning through their choice of modes and the interaction among those modes.

As shown in Table 3.5, we modified the design of the original manuscript to include a transduction column (3rd column). We also separated and reduced the density of images so that each image is associated with our transduction process. The result is a written account of the contributions of the verbal and non-verbal aspects of semiotic resources associated with the participant's interactions with each other and the tools in the environment.

Table 3.5

*Dialogue and Embodied Interactions Associated with Unit Movements**

Dialogue	Embodied Interaction	Transduction
B: We are doing less time, but more speed...	 [he moves hands like wheels of robot]	[→ to algorithmic thinking] The boy uses proportional reasoning to set the speed and time values for a 90° turn. His hands approximate the robot's wheels, with one hand moving forward while the other moves back.

** Also appears in Kopcha et al. (2020)*

Final Cycle. A deeper level of thematic analysis was required to show how the modes and semiotic resources contributed to the participant's meaning-making in a given context, with a particular focus on temporal organization of the participants' behavior (Hotton & Yoshimi, 2010). At this point, the goal was not to engage in frequency counting of the codes but rather develop a holistic understanding of the ways that the semiotic resources served as major tools of meaning-making in the context of robotics. This approach involved making generalizations based on the emergent patterns in the data and merging the prior themes and categories into one larger set of themes to address the research questions. The final interpretations from the data—in the final cycle of the researchers' consensus—indicated that (1) computational thinking was offloaded onto both the participant's bodies and structures in the environment and (2) computational thinking was guided by participant's embodiment of mathematical concepts (see Table 3.6).

Table 3.6

Themes From the Synthesis of A priori and Thematic Coding

Merging Emergent Themes & Categories*
1. Computational thinking was offloaded onto both the participant's bodies and structures in the environment. a. Basic robot moves b. Gestures c. The map and the computer d. The grid and the robot 2. Computational thinking was guided by participant's embodiment of mathematical concepts. a. Unit movements b. Multiplicative reasoning

**These themes are also presented in Kopcha et al. (2020)*

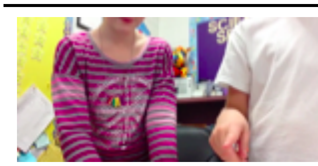
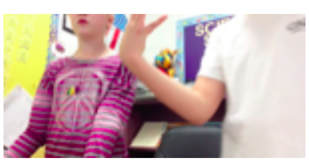
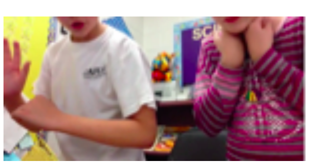
The Analysis of Embodied Interactions Through AI-enhanced Pattern Recognition. Artificial intelligence (AI) can support multimodal data analysis by evaluating large data sets to help identify images of interest, patterns of interaction, and the possible meanings behind those interactions (Sharma et al, 2019). Knowing that video excerpts have an enormous amount of detail that is easy to miss due to human error, an AI-enhanced pattern recognition approach was developed to facilitate the data analysis process as part of this study. For this analysis, the research team included the advising faculty member, Dr. Theodore J. Kopcha, and Raunak Dey, a Ph.D. candidate in the department of Computer Science at the UGA.

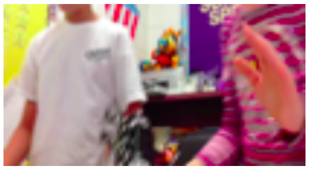
The AI analysis was approached as a qualitative research tool for multimodal data analysis. Even though multimodal transcription of video data offers a powerful way to research embodied thinking, video analysis is an overwhelming and daunting task for the number of reasons. A one-hour video can contain hundreds of potential images for coding and analysis; a researcher must therefore carefully review and select images that best reveal the meaning behind one's embodied interactions (Bezemer, 2014; Bezemer & Mavers, 2011). This can be laborious, since the images selected for analysis must clearly communicate both the behaviors and thinking behind those behaviors (Mondada, 2018). In light of this, video-analysis becomes an extremely sophisticated and time-consuming task for the researchers if done manually. Moreover, video excerpts have an enormous amount of detail that is easy to miss due to human error.

To ease the process of creating multimodal transcription, we sought to employ a deep learning AI algorithm to assist the video analysis and reduce the time and effort needed for manual labeling for the dataset. The deep learning AI algorithm created for this analysis entailed Keras and Tensorflow as tools to map the images that we already labeled during the manual coding associated with the grounded approach and the transduction process (see Appendix A for the technical report of the network design). The algorithm was then fed by data in the descriptive classification table data as displayed in Table 3.7. The process of training the AI and analyzing video is presented below.

Table 3.7

An Excerpt From the Manual Classification Table

Still Images	**Descriptive Label of the Still Images**
	[points to small map in workbook]
	[holds up four fingers as a numerical representation]
	[imitating the robot with arms at 90° angle]

	[participants hold the robot]

Manual Labeling. The first attempt to train AI involved creating a dataset of images extracted from the video excerpts. We created our initial dataset through the extraction of 2352 image frames that were randomly selected from a 10-minute video segment. We created a classification table by manually labeling the 2352 images. We created 25 categories for the dataset of 2352 images; the categories were created using a descriptive language that represented the human-tool interactions. An excerpt from the classification is displayed in Table 3.8 below. We selected one image as a representative of each category and fed this data to AI to see the preliminary results. The deep learning AI tools, Keras and Tensorflow, were used to create an algorithm to attend to the dynamicity of complex qualitative data that involve the analysis of collective social behavior through image recognition.

Table 3.8

Manual Classification for the Independent Interactions

Classification	Function	Context
Right hand parallel to the workbook.	Estimating the value of the variables: speed, distance, and time.	The precise estimation of speed: 0.5.
Right arm points at the monitor.	Tracing the failure back to its origin.	The failed code responsible for the robot's turn: he stated, *"that is where we take the turn."*
Right hand and right arm move left; left hand moves backward.	Making the right turn.	The imitation of the robot: he gestured to represent the right turn.

In the first trial, the AI was unable to learn due to the disproportionate number of categories used for manual coding compared to the number of samples. Simply put, there were not enough samples of pictures under each category. To address this, we reduced the number of categories to the five primary modes of interaction that emerged from the grounded theory, and increased the number of pictures for each category. The five categories addressed the participant's interaction with: (1) the workbook, (2) the robot, (3) their own bodies imitating the robot, (4) the computer, (5) and their physical representation of quantities (i.e., numerical representation).

The five categories were chosen purposefully. To be able to call mode a mode, speakers need to act on these resources meaningfully (Jewitt et al., 2016). Along similar lines, a mode is made out of "the actions and artifacts we use to communicate" (Van Leeuwen, 2005, p.3). In this study, a number of indicators were used to mark the use of semiotic resources as meaningful. The consistency of use was seen as one indicator of purposeful action; it was associated with the frequency of the behavior's emergence. The repeated action of participants was an encouraging factor to look for possible reasoning behind that action. This did not imply that an emergent mode was ignored based on its lower frequency count. Rather, the elicited function of the modes in the grounded approach was the major determinant of how the modes were selected to feed the AI. On the contrary, this study was concerned with every emergent mode related to the "tool use", namely the core variable. The modes that fell out of this range were simply not reported due to its irrelevance in addressing the research questions. For example, not every gesture produced by the participants provided an insight into the research questions; not every mode carried a communicative value.

Training the AI. After establishing the five categories, we then manually classified approximately 135 images within those major categories to train and test the AI. The training dataset involved: 28 samples for the workbook; 9 samples for the robot; 48 samples for the computer; and 17 samples for the numerical representation. The AI ultimately yielded 80% accuracy of match with our manual classification. The 20% inaccuracy was the result of some images lacking distinct, unique features altogether or a single image resulting in multiple possible categorization outcomes (e.g., she looks at the computer while he also moves like a robot's wheels).

Figure 4.3 presents the truth labels were displayed on the left while the prediction was placed on the right; and the bottom line represented the summary correct, total, % (i.e., 80%). The five classes were coded as follows: workbook: [0,0,0,0,1]; robot: [0,0,0,1,0]; imitating the robot: [0,0,1,0,0]; computer: [0,1,0,0,0]; and numerical representation [1,0,0,0,0].

Figure 3.4

The Visual Display of the Truth Labels

```
(array([0, 0, 0, 0, 1]), array([0.01217304, 0.00140641, 0.03665041, 0.        , 1.        ],
      dtype=float32))
(array([0, 0, 0, 0, 1]), array([2.9266805e-05, 1.9357228e-06, 1.4561087e-02, 0.0000000e+00,
       1.0000000e+00], dtype=float32))
(array([0, 0, 0, 1, 0]), array([1.0383282e-04, 0.0000000e+00, 3.3084176e-05, 1.0000000e+00,
       1.0227008e-04], dtype=float32))
(array([0, 0, 0, 1, 0]), array([0.0000000e+00, 6.8170101e-07, 8.1757090e-09, 1.0000000e+00,
       1.1531353e-06], dtype=float32))
(array([0, 0, 1, 0, 0]), array([3.5270514e-07, 1.9708584e-01, 1.0000000e+00, 0.0000000e+00,
       1.2114414e-03], dtype=float32))
(array([0, 0, 1, 0, 0]), array([1.2092181e-07, 7.0519286e-06, 1.0000000e+00, 0.0000000e+00,
       2.7588658e-02], dtype=float32))
(array([0, 1, 0, 0, 0]), array([2.0210858e-04, 1.7966072e-03, 1.0000000e+00, 0.0000000e+00,
       2.4145457e-01], dtype=float32))
(array([0, 1, 0, 0, 0]), array([2.6700931e-05, 1.0000000e+00, 2.7112640e-06, 0.0000000e+00,
       2.8806555e-04], dtype=float32))
(array([1, 0, 0, 0, 0]), array([1.0000000e+00, 1.8151298e-04, 9.7207826e-01, 6.7893684e-02,
       0.0000000e+00], dtype=float32))
(array([1, 0, 0, 0, 0]), array([3.7065128e-04, 7.1923489e-05, 1.0000000e+00, 0.0000000e+00,
       1.2906876e-05], dtype=float32))
(8, 10, 0.8)
```

Step 5: Draw Conclusions (i.e., Within and Cross Unit Analysis)

The **fifth step** Bezemer's framework is also the final step. In this step, the researcher returns to the initial research question and draws conclusions. In this study, this final step will entail both a within- and cross-unit analysis in which each of the approaches described above will comprise a case. Within-unit analysis will entail examining the results of each approach and evaluating the findings. The criterion for evaluation will draw from two major characteristics of complex dynamical systems: self-organization, emergence (Gallagher & Appenzeller, 1999; Richardson & Chemero, 2017). These characteristics, described below, are foundational to embodied perspectives of cognition and CT. Thus, the purpose of the within-unit analysis is to evaluate how well each approach attends to the constructs that are most important when examining children's CT from an embodied perspective. To guide this analysis, each case was analyzed to determine how the individual approach dealt with two prominent features of dynamical systems: self-organization and emergence.

Self-organization. Self-organization is "in service of adaptation to changing conditions" (Nathan & Swart, 2020, p.35). Therefore, in a complex dynamical system, feedback exchanged between the subsystems is one major factor determining the overall system's behavior—weight on an individual-being is being taken off the table in leading the system's behavior (Cilliers & Spurrett, 1999; Jacobson et al., 2016). A system's behavior therefore is not ruled by a central unit and/or an individual; instead it arises from multiple interacting components—this puts environmental interactions on the spot in shaping since collective social action.

Collective social interaction is mutually-constructed and multimodal, heavily relying on feedback-driven interactions between the human and environment. Likewise, CT develops in a system that constitutes verbal and non-verbal aspects of learners' interaction (e.g., bodily movements and tools). These interactions are temporally organized, as a function of time, due to the feedback exchanged within and across the interacting components (Berland & Wilensky, 2015; Kopcha & Ocak, 2019). This makes the boundaries of a complex dynamical system pliable and softly-assembled due to the momentary organization of behavior, ever-evolving dynamics (Richardson & Chemero, 2014). One challenge therefore is to determine the system's boundaries, what to call as a unit of analysis. In other words, an inevitable concern of how to sort out the learning phenomenon of being studied while it is having such flexible boundaries.

This complexity gives rise to another persistent research concern such as deciding whether participants' interactions were part of a self-organizing system, and if so, how to display this self-organizing nature in a multimodal transcript. First of all, over the last half century, some attempts have been made to model the behavior of dynamical systems (Kugler et al., 1980). These models have been particularly useful to understand whether a system is interaction-dominant and/or self-organizing, and to what extent a system is decomposable or non-decomposable to be studied as a function of its subcomponents. (see Favela & Chemero, 2016). This particular research of Holden et al. (2009) provided direct empirical evidence of how cognitive systems are interaction-dominant, multimodal, and extended beyond the boundaries of the body (as cited in Favela & Chemero, 2016). Favela and Chemero (2016) also cite from Dotov et al. (2010) to provide empirical evidence of how human beings that are coupled with tools constitute an interaction-dominant system in itself. Therefore, it is not this dissertation's concern to confirm whether the participants' interactions were part of a self-organizing system, rather to display to what extent the given approaches help reveal self-organizing nature in a multimodal transcript and how much this would contribute to our understanding behind the development of computational thinking.

Even though there is no single way of addressing this concern, approaching a research phenomenon that is softly assembled unequivocally involves a combinatory of scale-down and scale-up approaches (Nathan & Swart, 2020). Scale-down approaches help seclude the research phenomenon, while the scale-up approaches help draw general conclusions grounded in data. Scale-down approaches are more sensitive to detect micro-level changes that happen in the data because it allows fine-grained analysis of the meaning that a mode conveys over time. However, understanding the shift across the modes is not easy because people bring a variety of modes into play during reciprocal dialogue as part of their meaning-making process. Goffman (1974) recommended recording nuances, such as the slightest shifts in the tone of voice or bodily orientations to mark continuities and/or discontinuities in the data. Overall purpose therefore is not to generalize, rather to detect and/or contextualize the changes as a result of feedback-based interactions of interacting components (Jacobson et al., 2016). This allows researchers to map out a self-organizing system as a function of displaying (1) how learners' move across modes over time, and (2) the aspect of emergence.

Emergence. Emergence, then, is another important aspect of a complex dynamical system. Emergence refers to the way that the overall system displays a behavior that cannot be anticipated based on the behavior of its components. For example, Kopcha et al. (2020) found that children's direct interaction with an educational robot resulted in development of their mathematical intuition in which they discovered an action pattern between time and distance: "she predicted that "a small increase in time (i.e., 0.3 seconds) will result in a corresponding small increase in the distance the robot travels" (p. 25). This revealed how CT was actually guided by participant's embodiment of mathematical concepts and the way the robot's movement emerged over time. This finding is an indicator of a significant trait of any dynamical systems—emergence—where the overall system displays a behavior that is different from its components. Emergence therefore could be revealed in the analysis by examining the results of each approach and then synthesize the categories to enlarge the web of causation.

Within-unit analysis will therefore begin by reviewing the methods of data collection and analysis associated with each analytical approach, as well as presenting the key results. As shown in Table 3.9, this process will entail constructing a written summary detailing how each approach helped reveal the self-organizing and/or emergent aspects of the phenomena of interest. For example, each approach will be examined to determine how the temporal and spatial organization of the behavior was transcribed to reflect the self-organizing nature of the system. This will be accomplished through coding for temporal and spatial organization of the behavior in the multimodal transcript. The descriptive account of the modes drawn from the video data will be dissected into micro-level fragments—using scale-down approaches—to conduct a fine-grained analysis of multi-semiotic resources. Jotted down the thoughts, notes, and reactions to the data—as suggested by Merriam (2009, p.178)—will be integrated into the constructed summary during within-unit analysis. The results will be organized in the form of Microsoft Word tables and representative figures. In addition, each approach will be examined to determine the extent to which the analysis accounted for learners moving across different modes.

Table 3.9

Criteria of Within and Cross-unit Analysis in Terms of Complex Dynamical Systems Theory

	Characteristics of Interest	**Technique**
Self-organizing system	Micro-level, scale down approaches ● Coding for order of social interaction ● Coding for temporal and spatial organization of the behavior	● Stripping the layers of data to the micro-level in search of possibly interconnected causes that leads to the research phenomenon. ● Displaying how participants' move across modes over time.
Emergence	Macro-level, scale-up approaches ● Synthesizing a priori codes and categories for covert themes ● Holistic view of system's changing behavior	● Merging the prior themes and categories into one larger set of themes to address the research questions.

For the cross-unit analysis, macro-level, scale-up approaches will be used. This will entail looking across the results of the within-unit analysis and organizing them into initial categories and themes. As recommended by Yin (2009), this will include creating a comparison table using a Microsoft Word table (or similar) that supports "the analysis of the entire collection of word tables...to draw cross-case conclusions" (p.135). Following Yin's recommendation, the integrative table will summarize the entire case, present the relevant results, and address the research questions driving the study.

The purpose of looking across cases is to determine the strengths and/or weaknesses associated with each approach as compared to the other approaches. Thus, the cross-unit analysis will be guided by comparing the extent to which the method and results reveal the self-organizing nature of a complex system and contribute to our understanding of the development of computational thinking. This will help other scholars because it will reveal the application of the theory—that draws from the central teaching of radical embodiment—in which CT as cognitive activity is extended beyond the boundaries of the body.

Subjectivity Statement

As a junior researcher, I bring different subjectivities to my research. First and foremost, embodied cognition has been the focus of my studies since my first year as a doctoral student. That being the case, my philosophy of learning is extensively grounded in the phenomenology of the lived body, the roots of which extend back to Merleau-Ponty (1962, 1965), who is the father of embodiment. Therefore, I will avoid interpreting data in a way that it implies the idea that "the mind presents and computes"; which dismisses the body's place in the real world; so its coupling of the environment (Branquinho, 2001, p. 15). As a result, all my interpretations during data analysis will be under the significant influence of the embodied perspectives; I will draw predominantly on learning as an embodied activity. To constantly check and be aware of my predispositions, peer debriefing will be conducted throughout the data analysis process.

I am also compelled to explore embodied cognition in a narrowed down fashion, with the focus on socio-cultural perspective (Gibson, 1977, 1979/1986; Goodwin, 2007; Goffman, 1964). Socio-cultural perspectives suggest that learners' embodied interactions are socially and culturally situated, and it has to be interpreted accordingly. During embodied interactions, participants make use of a variety of modes as they co-construct a reciprocal dialogue. These modes might vary in shape as they are seen as different forms of communication (e.g., gestures, discourse). The meaning that a particular mode encapsulates, therefore, would change as the users act upon it. In other words, semiotic content re-forms as a result of goal-oriented performance. As a result, I draw on this dynamicity in the design and creation of a multimodal transcript.

My interest in exploring computational thinking as an embodied phenomenon stems from the research work in matters related to the design and implementation of the STEM-integrated robotics curriculum, one of Research And Innovation in Learning (RAIL). As a member of RAIL, I designed and delivered an embodied robotics curriculum to examine the impact of robotics education on elementary school students' understanding of mathematics and computational thinking. This experience taught me that every pair of learners has a divergent pattern of learning as they engage in computational thinking. This encouraged me to look for numerous patterns and conduct within- and cross-unit comparisons to explore embodied learning patterns. This was the main reason to pair learners as they engage in robotics activities.

The research design has also been under the significant influence of my research background in video-based research. I have been greatly engaged with video-based research a priori, which made me aware of possible strengths and limitations in identifying the video camera set-up and assigning data collection sites. For example, video footage is a represented world; it "limits the information recorded to that amenable to audio capture and camera work" (Dicks et al., 2006, p.78). That being the case, collection of video and audio data will be supported by the analysis of learners' artifacts to draw a more holistic picture of learners' engagement with the environmental structures (e.g., robot, the grid) and to reveal social and cultural practices.

To sum up, I take part in this study as a data collection and analysis instrument for the intended study. The listed assumptions, beliefs, and subjectivities have enormously oriented the research design. I believe that I fairly map out my identity as a researcher and provide transparency through the record of my assumptions and subjectivities.

Ethics and Confidentiality

In the intended study, Institutional Review Board (IRB) protocols were followed. The electronic web application of the IRB Portal granted the allowance of working with human subjects. For the video-recordings, participants gave their consent to be recorded. The participants were reminded that any information related to their identities are not to be disclosed. The participants were ensured that their identity would be protected at all costs.Besides, in any ensuing publications, all the names are going to be replaced with their pseudonyms, and participants' faces are blurred. Overall, I do not anticipate any risks from participating in this research. The data stored in a protected folder. The access was granted to the researchers who completed the CITI training.

Trustworthiness of the Study

Consensus building, peer debriefing, and thick descriptions are the primary methods to ensure rigor and trustworthiness of the study. According to Anafara et al. (2002), public disclosure of the data collection and analysis process and thick descriptions ensure the validity of the research in qualitative research. Providing as many details as possible while reporting the details of data collection and analysis is a good practice for granting transparency of the study . Moreover, consensus building offers a way of checking whether the interpretation of the data complies with the participants (Tracy, 2010). Consensus building involved rigorous work with the advising faculty member and graduate researchers to draw a more complementary picture in addressing research questions.

CHAPTER 4

Findings and Discussion

The overarching purpose of the study was to explore how different approaches to the analysis of multimodal transcripts can reveal the embodied aspects of children's CT, and how those approaches differ. As a reminder, the overarching question driving this study was: *How can embodied perspectives be leveraged into a research methodology in the area of children's CT?* This question was explored through a within-unit analysis that answered these three sub-questions first:

1. How does a grounded approach to analyzing a multimodal transcript approach the study of children's CT as an emergent and self-organizing phenomenon?
2. How does a process of transduction with a priori coding and thematic analysis approach the study of children's CT as an emergent and self-organizing phenomenon?
3. How does an AI-enhanced pattern recognition approach approach the study of children's CT as an emergent and self-organizing phenomenon?

The within-unit analysis also examined the extent with which each approach addressed two characteristics of complex, dynamical systems in the context of children's CT: self-organization and emergence. The within-unit findings then supported a cross-unit analysis in which the affordances and limitations of each approach were explored. Thus, this study addresses a fourth sub-question:

4. What are the key strengths and differences associated with the three different approaches to the multimodal analysis of children's CT?

The results of the within- and cross-unit analysis are presented in the sections that follow. The findings are organized such that the overall results are both presented and discussed within the same section. This organization was selected to aid readability, so that the reader may better understand the significance and importance of each set of results as they are presented.

Within-unit Analysis

This section summarizes the major findings associated with each analytical approach—that is, with the grounded analysis, the transduction approach, and the AI-enhanced approach. . Prior to conducting a cross-unit analysis, the discussion of embedded subunits is first provided, and then the findings from each unit are framed through the lens of complex dynamical systems theory. Table 4.1 provides an overview of the within-unit analysis to walk the readers through each approach. The table serves as a guide to display how each method dealt with complexity by addressing the guiding questions. The table is organized by the features of complex, dynamical systems, including self-organization and emergence.

Table 4.1

Major Features of Complex Dynamical Systems and Implications for Cross-unit Analysis

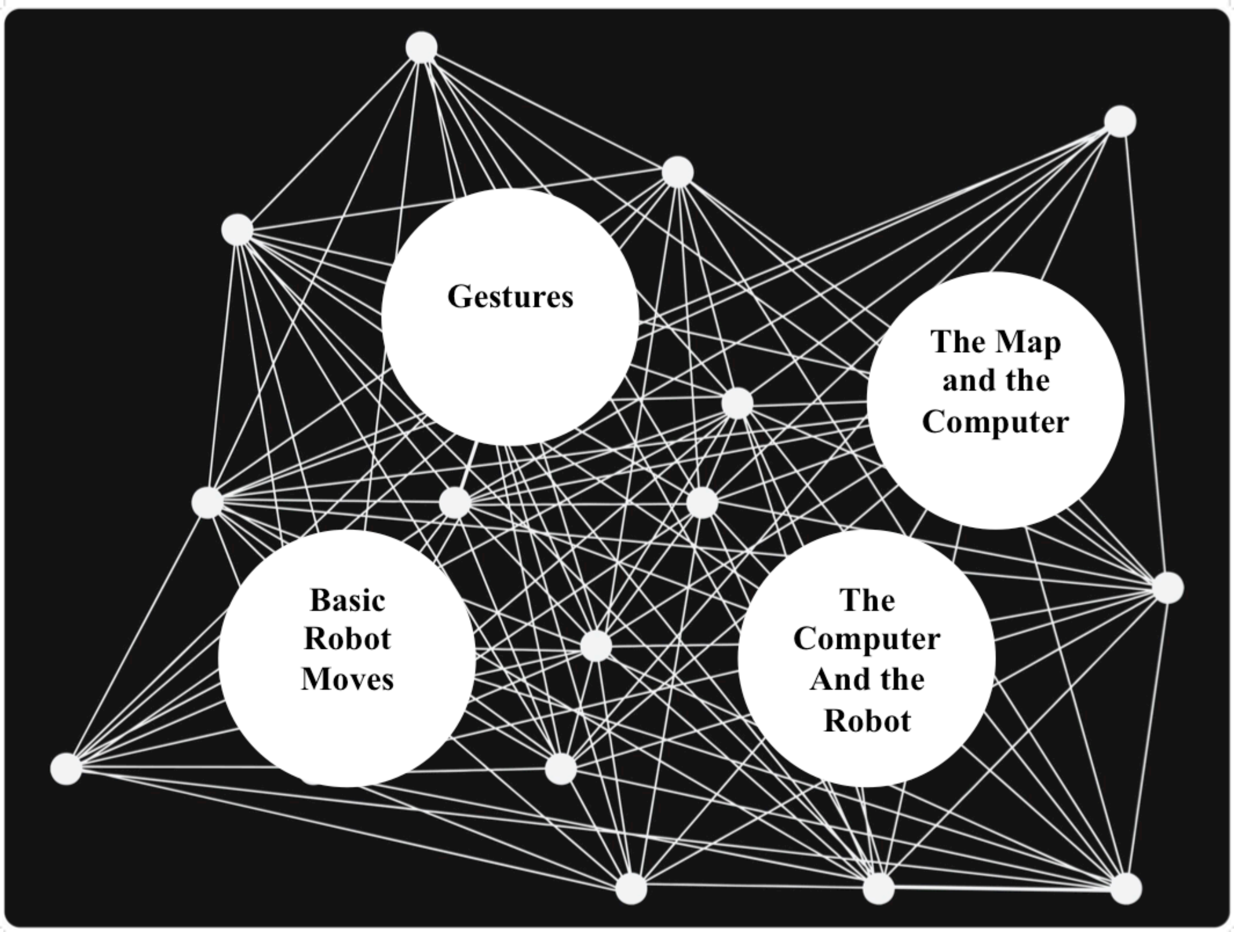
	Grounded approach to analyzing a multimodal transcript	**Transduction with a priori coding and thematic analysis**	**AI-enhanced pattern recognition approach**
Self-organization	The method helped identify the subsystems that are nearly decomposable: What was the central mode in the web of causation?	The method helped identify the interpretation of the interplay of the subsystems: How did participants move across the modes? What story did the interplay of different modes tell?	The method helped classify the embodied interaction under the designated modes. What type of multimodal interactions did the AI identify in an individual frame?
Emergence	The method helped identify the basic moves that build up to more complex movements: What were the agent-level behaviors?	The method helped interpret the order behind the chaos through the analysis of aggregate level behaviors: What was the reasoning and/or glue that guided the deliberate decomposition of the task?	The method helped identify the multiple interactions in an individual frame: What were the multiple modes of interaction do the participants participate in a particular scene?

RQ1: How Does a Grounded Approach to Analyzing aMultimodal Transcript Approach the Study of Children's CT as an Emergent and Self-Organizing Phenomenon?

In this study, the first methodological approach to the analysis of our multimodal transcript was a grounded approach. As explained in the Literature Review, Chapter 2 of this dissertation, the grounded approach is a prominent qualitative research method that enables near-decomposition of an overall system into its functional parts. In this study, the grounded approach offered a good start to the analysis of the collective social behavior of the participants. The analysis first focused on the identification of the central mode of interaction (i.e., core variable) and the other modes interconnected to the core variable. As shown in Figure 4.1, the process of children's computational thinking (CT) was broken down to reveal the interactions within the components of the system and the function of those components.

Figure 4.1

The Grounded Approach Featuring the Interactions Within the Components of the System



The focus on exploring CT through its unique components revealed that the grounded approach was well suited for the self-organizing nature of CT. However, the grounded approach lacked attention to the interactions *across* components (i.e., the web of interaction, see Figure 4.1), making it less suited for capturing the emergent nature of the system as a whole. The findings, which appear in more detail below, also appear in Kopcha and Ocak (2019); those findings are summarized here in an effort to open a broader discussion about the method of analysis rather than Kopcha and Ocak's (2019) previous focus on specific cognitive outcomes.

Interactions Within the Components of the System. The grounded approach revealed *tool use* as a core variable. Tool use refers to the dominant form of interaction present in the data — the participants regularly and repeatedly used their own bodies, the robot, and other structures in the environment to engage in CT. Deeper examination of this core variable revealed two aspects of CT as a dynamical system. The first was the identification of the specific modes (i.e., tools) that were present during children's computational thinking. The primary modes of interaction were identified as (1) basic robot moves, (2) gestures, (3) the map and the computer, and (4), the grid and the robot. The second was the elicitation of each mode's function in the context of CT. These modes are presented below, and also displayed in Figure 4.2.

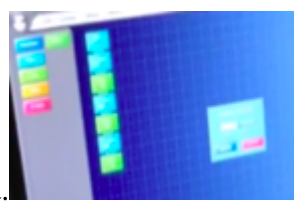
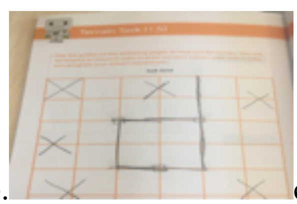
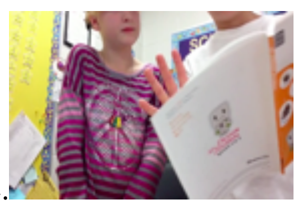
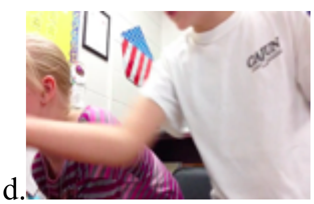
Basic Robot Moves. The basic unit movements were one of the primary modes of interaction. The participants created (1) a forward unit square, and (2) a 90-degree turn to successfully traverse the robot at 6x6 coordinate grid: The unit square to move the robot one of the squares on the grid; a 90-degree turn to maneuver the robot. The pair learned to move the robot forward two units by programming a movement speed of 0.4 for 1 second in the coordinates of the grid.

Gestures. The gestures were the participants' bodily representations of knowledge during the collaborative work. It involved the learner's hand and body movements; a broad range of gestures was observed during the reciprocal dialogue. The semantic context framing the gestures were used to classify the participants' hand and body movements such as (i) moving forward the distance of one unit square, (ii) stopping for a moment, (iii) making a 90° turn, (iv) moving hands apart to show the distance traversed over a fixed length of time (i.e., 1 second), and (v) rolling hands 2½ times to indicate the number of units.

The Map And The Computer. The participants created a miniature replica of the 6x6 larger coordinate grid so that they could work at the computer without returning to the grid and also without relying solely on memory.

Figure 4.2

The Primary Modes of Interaction in the Context of Robotics

a.  b.  c.  d. 

The Computer And The Robot. The computer program involved the visual block coding computer program. The pair used the computer to program the robot and the robot executed the code via moving forward and maneuvering at the 6x6 larger grid.

The Function of Each Component. The grounded approach enabled an in-depth exploration of the function that each tool served for the participants as part of their computational thinking. Table 4.2 displays the function that each tool served. The grounded approach was helpful to elicit these functions because each tool represented a different mode of meaning-making for the participants in the study. For example, the map and computer, together, served as a conjunctional mode in that they were a physical representation of the participant's thinking. These modes helped the participants "visualize movements from the code itself and then attempt to act those movements out to determine if they would be effective" (Kopcha & Ocak, 2019, p.6).

Table 4.2 displays the findings from the micro-level analysis. These findings offered insight into how each tool functioned in a particular context, depending on the participants' immediate goal. The grounded approach was helpful to elicit these functions; for example, "the map and computer together served as a physical representation of their thinking; they would visualize movements from the code itself and then attempt to act those movements out to determine if they would be effective" (Kopcha & Ocak, 2019, p.6).

Elicitation of these functions was achieved by selective coding. The selective-coding process helped build relationships between the categories encircling the core-variable (Birks & Mills, 2011; Johnson & Parry, 2016). As a result, each mode (i.e., gestures) was explored in terms of its joined modes of interaction, which in turn provided the function of the mode of exploration. In the context of gesturing, microanalysis of the participants' discourse revealed the essence of reciprocal dialogue; the interpretation of the gestures, therefore, was achieved by the semantic context that framed gestures.

Table 4.2

Function of Each Mode Described by Kopcha and Ocak (2019)

Mode	**Function**
Basic Robot Move	"These basic moves served as tools for communicating the overall solution path." (p. 4)
Gestures	"The gestures largely served as a re-enactment of the robot's movement at the grid. The gestures helped the participants gain the perspective of the robot, specifically when debugging the solution and reprogram the robot's movement." (p. 5)
Map and Computer	"The participants combined the visual block coding (i.e., computer program) and a small, hand-drawn map to serve as a tool for supporting their collaborative problem-solving (see Figure 4a and 4b)." (p. 6)
Robot at the Grid	"As the participants viewed the robot at the grid, they watched to see whether the robot's movements aligned with their overarching solution path for completing the task. To the extent that those movements did not, the participants returned to their other affordances (e.g., gestures; the map and computer) to debug their program or revise their intended goal in a collaborative fashion." (p. 6)

Self-organization and Emergence. The grounded approach provided an in-depth description of each tool (e.g., basic robot moves, gestures), and the ways in which participants acted upon these tools—that is, the function of the tools for our participants. In this way, the fine-grained analysis of the moments revealed the self-organizing nature of children's CT in that it focused on the interconnectedness of the modes in the *within-subsystem interactions* (i.e., unit movements). It highlighted the fact that gestures carry a semantic value, and gestures are environmentally tied (Alibali, 2005; Goodwin, 2017). Without the analysis of the self-organization of environmental structures, the meaning behind the gestures would not have been understood. In this sense, the selective coding process was efficient in building connections among different modes of meaning making as they became organized in our context. Figure 4.3 displays the self-emergent and interconnected nature of the modes of meaning making in the context of CT; the images illustrate how the boy used his body to imitate different structures in the environment while explaining his thinking (e.g., the robot, numbers in the computer program, distance on the grid). The boy's gestures represented the movement of the robot when it was (a) moving forward the distance of one unit square, (b) stopping for a moment, and (c) making a 90° turn, (d) indicate the speed setting in the computer program.

Figure 4.3

The Boy's Bodily Representations of the Robot's Movement

In addition to the interdependence of gestures and discourse, the findings from the grounded approach revealed that gestures were also coupled with the use of external tools: the map and computer. These external information-bearing resources served as the embodiment of the participants' thinking. Through the manipulation of these tools, the participants displayed a form of perspective taking in which they visualized the robot's movement from the code itself or other environmental structures associated with the robot. These findings, once again, offered strong evidence of the interconnectedness of the modes by grounding every mode in relation to the others. In light of the findings above, it can be argued that the grounded approach was efficient in identifying within system interactions, namely the semantic value of each mode in connection to others. In other words, the grounded approach revealed the primary modes of interaction (e.g., open-coding) while also eliciting the emergent and interconnected function of the modes (e.g., selective-coding) in the context of the children's CT.

What was missing, though, was a more comprehensive exploration of the interactions across the components of the system. We knew that certain modes (e.g., gestures) became a tool for deliberate decomposition of the overall solution path; however, we did not know why the participants chose to use their bodies to imitate the robot's actions (e.g., hand-mimicking the robot's turn) during the negotiation of the task's decomposition. For example, the data revealed that the girl retraced the path that the robot followed at the large grid with her hands by drawing an imaginary path on a smaller hand-drawn map. While this suggested she was decomposing the steps to achieve their next goal, we did not know why she chose the small map and complemented it with her gesture at this specific moment.

The fact that the grounded approach lacked a more comprehensive exploration of the across-component interaction suggests that the approach did not fully reveal the emergent nature of CT in this study. Near-decomposition was effective in identification of within tool interactions; what type of human-tool interactions emerged within the near-decomposed parts of the overall system. To understand the emergent elements of the system, the approach would also need to critique why the pair prioritized one mode over another. As noted by Nathan and Swart

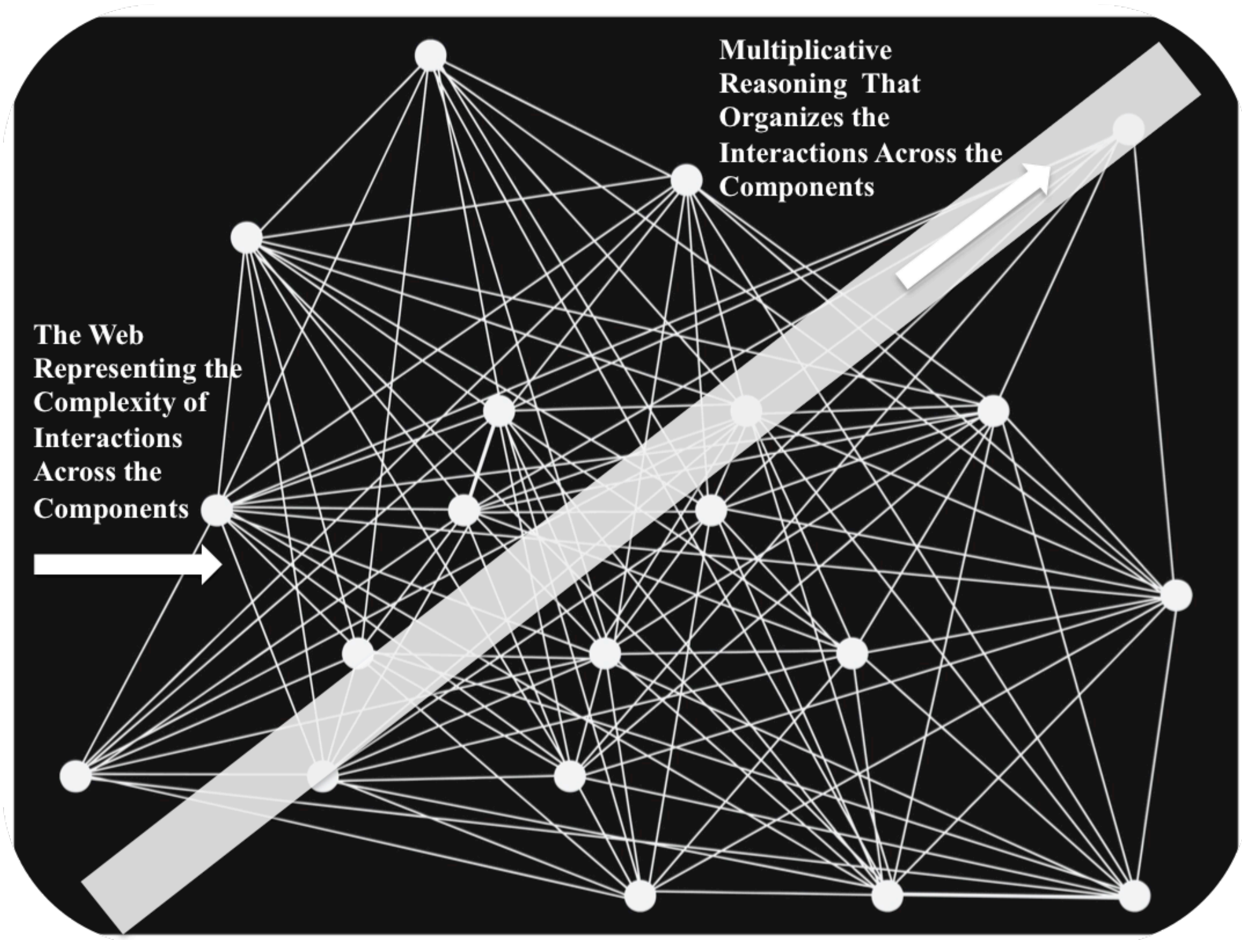
(2020), this shortcoming of the grounded approach is not unexpected. Grounded approaches are meant to take a scale-down approach, where a complex system is broken into its within-system parts. To understand how participants prioritized one mode over another would require a scaling-up technique that is, in many ways, counter to the purpose of a grounded approach.

RQ2: How Does a Process of Transduction With a Priori Coding and Thematic Analysis Approach the Study of Children's CT as an Emergent and Self-organizing Phenomenon?

In this study, the second methodological approach to the analysis of our multimodal transcript was a transduction. As explained in the Literature Review, Chapter 2 of this dissertation, transduction is an analytical approach that seeks to understand the meaning behind social interactions by looking across modes (Jewitt et al., 2016). In this study, the process of transduction revealed the temporal and spatial organization of modes — in any given moment, the participants drew on and used various modes of interaction. The analysis first focused on how different modes (e.g, discourse, gesture, tool use) organized in a given moment and over time; this helped reveal the meaning behind the participants' social interaction in the context of CT (Bezemer, 2014; Mondada, 2018). Specifically, the process of children's computational thinking (CT) was explored by looking across modes to reveal the reasoning behind the participants' spatial and temporal organization of modes of meaning-making, as shown in Figure 4.4.

Figure 4.4

The Transduction Approach Featuring the Interactions Across the Components of the System



The Figure 4.4 depicts how the interactions across the components were at the heart of the transduction. For this reason, transduction is well suited for studying CT as a dynamical system in that it seeks to understand how the self-organizing aspects of CT emerged through embodied interactions. The findings associated with the transduction approach revealed the emergence of multiplicative reasoning as a guiding component of children's CT. Those findings, which appear below, also appear in Kopcha et al. (2020); in this study, those findings are summarized to open a broader discussion about the method of analysis rather than the previous focus of Kopcha et al. (2020) on specific cognitive outcomes.

Temporal and Spatial Organization of Modes. The learner's temporal and spatial organization of modes revealed how the pair drew on and used various modes of interaction in a given moment. Table 4.3 displays an excerpt from the multimodal transcript that shows the way that the participant's *move-across modes* when decomposing the task on-the-spot to decide the robot's next move. These transitions became more transparent through the side-by-side organization of the dialogue, and the gestures that were organized to coincide, temporally, with the dialogue. In this way, the transduction told a coherent story of *moves across modes* by explaining how the participants chose "the most apt signifier to represent the meaning signified" (Dicks et al., 2011, p.229).

Table 4.3

*Displaying the Complexity Through Move-across Modes**

Dialogue	Embodied Interaction	Transduction
B: That was perfect! G: Now we need to turn… B: ...left. So that means right forward, left backwards...speed of 4 for point four.	 [she looks at computer, he moves like robot's wheels]	[→ from testing] The pair returns from a successful test. The girl continues decomposing. The computer program serves as a focal point as the boy moves from decomposing to algorithmic thinking. His hands move like the turning wheels of the robot. Her use of **"we"** suggests that they continue to think as if they and the robot are one in the same.

** Also appears in Kopcha et al. (2020)*

The way that the participants' *move-across modes* was displayed through the interplay of the modes of interaction, as it was detailed in the transduction. For example, the participants combined different semiotic units to make meaning, ranging from their gestures (e.g., his hands move like the turning wheels of the robot) to its complementary discourse (e.g., he utters, *so that means right forward, left backwards*). In the meantime, the computer program also served as a focal point during solving the problem (e.g., the girl's leaning towards the computer screen). The coupling that was taking place among the gestures, discourse, and environmental structures were constantly changing as a result of the participant's adaptation to the changing learning conditions (see Appendix B for the moment that indicate environmental coupling). This dynamic change amongst the modes was reported in the form of the researchers' narrative in the transduction.

The unpredictability of the participants' *move-across modes* predominantly marked the dynamicity of how CT developed (Favela & Chemero, 2016). The whole process was dynamic because *moving-across modes* could not be predicted prior to the event due to its exclusivity to the participants' temporary social interaction. This complexity was also evidently displayed and addressed in the rest of the multimodal transcript (see Appendix B). For the reasons discussed above, the transduction played its part in guiding researchers to display interdependent interactions from one mode to another.

In this study, transduction also has been a promising tool to reveal underlying, yet covert order in the data that informs participants' shift across different modes of meaning making. Through transduction, I looked at how different modes (e.g, discourse, gesture, tool use) organize in a given moment and over time to reveal the meaning behind those modes (Bezemer, 2014; Mondada, 2018). The thematic analysis of the transduction revealed that one of the biggest findings associated with the learner's move across modes guided by their embodiment of multiplicative reasoning. This finding was significant in terms of its contribution to the behavior of the overall system and in understanding how the components of the system related across the system.

Self-organization through Multiplicative Reasoning. Unlike the micro-level (smaller scale) interactions of the various modes revealed through the grounded approach, the transduction column supported the exploration of events at a macro-level. This was facilitated by merging the findings from a priori coding and thematic analysis of the transduction to add another critical tier to the participants' emergent behavior, which was the development of "thinking in multiplicative quantities" (Kopcha et al., 2020). Two types of multiplicative reasoning became apparent in the transduction; one was a perceptual approach to proportional reasoning, and the other was the multiplicative halving and doubling of quantities. Both were rooted in the participant's early development of unit movements, which formed a foundation for their proportional reasoning.

The Unit Movements. Initial conceptualization of the robot's movements in a coordinate grid (i.e., 2 units: 1 second) later caused development of learner's multiplicative reasoning. This type of reasoning supported the participants to move the robot using the coordinates of the grid with precision. The initial unit movements focused on two actions of the robot, one for moving the robot forward and one for turning the robot.

Multiplicative Reasoning Perceptual Approach. A perceptual approach was an emergent strategy that supported the participants' development of computational thinking. The participants drew on their embodied reasoning that was grounded in the discovery of the relationship among interdependent measures of a system. For example, the participant's body played an integral role to foster emergent perceptual reasoning; she rolled her hand 2½ times to indicate the number of units that the robot will move (see Table 4.4).

Table 4.4

Emergent Perceptual Reasoning

Dialogue	**Embodied Interaction**	**Transduction**
G: And then we want to go forward for twenty-five hundredths [of a second].	 [she rolls hands]	[→ to decomposition and algorithmic thinking] The girl conceptualizes the next movement. Her gesture reflects numerical precision; she rolls her hand 2½ times to indicate the number of units that the robot will move. The way that the gesture corresponds with the girl's thinking suggests she is using her body to support abstract mathematical thinking.

* *Also appears in Kopcha et al. (2020)*

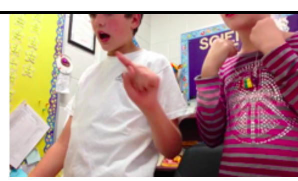
The side-by-side analysis of learner's choice of modes—that is, the discourse and gestures—helped to reveal the emergent nature of their multiplicative reasoning. Specifically, it emerged when the participants used "the original unit movement (i.e., 2 square units for 1 second)" and realized that it "did not move the robot far enough to achieve their goal" (Kopcha et al., 2020, p. 22). This led to an emergent, visual form of perceptual reasoning that involved making rough estimations about the robot's next movement. In the excerpt, the boy's reasoning was perceptual, solely based on the robot's movement at the grid: [it] "went too slow". The solution was as perceptual as the problem: "the [time] needs to go higher". At the same time, the learner's gesturing was complementary to their discourse; he thrusts finger forward and upward in one motion (i.e., upward motion implies an increase). The type of reasoning captures how CT was emergent in this context; the side-by-side analysis of the modes helped reveal the underlying relationship that connected those modes—that is, the proportional relationship between distance and time (e.g., And then, we went too slow. So, the [time] needs to go higher).

Multiplicative Reasoning: Halves and Doubles. Halves and doubles emerged as another strategy for conceptualizing one length or distance in relation to another as a function of time. The participants created new movements by tailoring the original unit movement (i.e., 2 units: 1 sec → 1 unit : ½ sec → ½ unit : ¼ sec) by halves and doubles. Halves and doubles eventually supported the deliberate decomposition of a task to achieve the desired movement of the robot with precision.

The pair's perceptual reasoning was followed by a precise estimation (e.g., adding 0.3 to the original unit movement) as displayed in Table 4.5. This time with the transduction column, we found that the participants created new movements (e.g., halves & doubles) by tailoring the original unit movements. Twenty-five hundredths [of a second] (i.e., 0.25) is the representative of the "repeated reduction of the original unit movement by halves" (i.e., 2 units: 1 sec → 1 unit: ½ sec → ½ unit: ¼ sec) (Kopcha et al., 2020, p. 23). This finding particularly came into the light with the simultaneous analysis of the girl's gestures; rolling hands 2½ times implied the multiplicative relationship between the variables.

Table 4.5

*Precise Estimation of Distance**

Dialogue	**Embodied Interaction**	**Transduction**
B: And then, we went too slow. So, the [time] needs to go higher. So, try 1.3? G: Yeah, 1.3.	 [he thrusts finger forward *and* upward in one motion]	[→ to algorithmic thinking] The boy then points and moves his arm forward and up at the same time. The gestures suggest he is thinking about how an increase in time value will correspond with an increase in distance travelled. He confirms

		the girl's suggestion of adding 0.3 to the original unit movement.

* *Also appears in Kopcha et al. (2020)*

In another example, the boy doubled the amount in an attempt to move the robot four unit squares forward: his discourse and gestures mutually advanced each other: He stated: "because two [units] would be one second, so four would be two [seconds]", while holding up four fingers, and pointing at the map. Given all these examples, the participants developed perceptual reasoning by predominantly situating the concepts in their embodied interactions within and across system's levels. Table 4.6 down below provided a supporting example from the multimodal transcript.

Table 4.6

An Excerpt from the Participants' Self-organization of Modes

Emergent Behavior	**Participants' Self-organization of Modes**
Unit Movements	The boy"draws on the unit movement for moving forward: "Now we need to go forward one second at speed 5." As he speaks, he points at the small map. This suggests he is decomposing the task while also determining the speed and time values needed to move the robot with precision (i.e., algorithmic thinking)" (p.19)

Multiplicative Reasoning: Perceptual Approach	"The participants return from testing and realize that the original unit movement (i.e., 2 square units for 1 second) did not move the robot far enough to achieve their goal... the girl conceptualizes a possible solution in which the robot needs to "go faster," where "faster" refers to the timing of the movement (i.e., "...not [speed] faster")" (p.22).
Multiplicative Reasoning: Halves and Doubles	"The pair attempts to move the robot forward four unit squares. The boy recognizes the distance as being two forward unit movements and doubles the time value: "Because two [units] would be one second, so four would be two [seconds]." At the same time, he holds up four fingers, then points at the small map. These actions suggest that he is performing a mathematical calculation while also conceptualizing the effects of that calculation at the same time." (p.24)

Emergence and Self-organization. The process of transduction addressed the self-organizing and emergent nature of CT in several distinct ways. The first was in the way transduction resulted in various displays of the participant's move-across modes. The primary mechanism for this was the third column that was added to the multimodal transcript. That column contained a researcher-generated, holistic account of the shifts in modes whose meaning could be analyzed in a given moment as well as over time. This not only helped reveal how the modes became organized by the participants (i.e., self-organization) but also insight into the meaning behind that organization that emerged over time (i.e., emergence).

This finding suggests how one strength of transduction over the grounded approach was the manner in which it revealed the emergent aspects of children's CT. Unlike the grounded approach, the transduction process indicated "how gesture and language mutually advance one another in a complementary fashion" (see Kopcha et al., 2020, p.7). The side-by-side organization of the participants' speech,their bodily representations of their thinking, and the researcher's holistic summary of the move-across the modes eventually revealed how multiplicative reasoning played an important role in explaining the children's use and prioritization of modes over time. This reflects how transduction can support a researcher in taking a scale-up perspective in which the behavior of a system is understood by looking across the various components of that system.

In creating the arrangement of verbal and non-verbal modes in our transcript, we knew how the different tools were brought into play by the participants. Whereas the grounded approach helped reveal the function of the tools, transduction placed the emphasis on the reasoning that brought the modes of meaning-making together within the larger system. The key to reveal this reasoning was the temporal and spatial organization of the discourse around the images. This alignment was significant in revealing the emergent patterns connected to the development of CT.

The shifts across the modes originated from the participants' "cognitive dissonance" (You, 1993, p.24); when one mode of expression did not meet the participants' source goal, it either had to be diminished or complemented with the other modes. The findings from transduction provided an abundance of evidence about how this dissonance played a role in the modes that were used and how those modes shifted over time. In one of the scenes of the multimodal transcript (see Table 4.5), the participants observed that the unit movement did not move the robot in the right amount; therefore, it had to be tailored. The discrepancy that arose from the misalignment between what the participants initially planned and what they accomplished in reality resulted in the conceptualization of possible solutions such as going faster or a small increase in the distance the robot travels. The transduction process efficiently attended the moments of failure (i.e., discrepancies) that resulted in tailoring the unit movements and/or the shifts across the different tools robotics (i.e., from the workbook to the grid).

RQ3: How Does AI-enhanced Pattern Recognition Approach Approach CT as Emergent and Self-organizing?

Our AI-enhanced pattern recognition analysis was devised as a qualitative research tool to deal with the complexity that manifests during the fine-grained analysis of video data. Artificial intelligence is a rapidly growing field in which computers and robots are called upon to assist humans in complex cognitive tasks. As noted by Toivonen et al. (2019), AI has been used in a variety of ways, from supporting doctors in making medical decisions to creating robots that perform advanced human functions (Mintz & Brodie, 2019; Siau & Wang, 2018; Patrício & Rieder, 2018). The idea is that AI can augment human performance in ways that extend our decision-making and data analysis capabilities (Toivonen et al., 2019).

This study attempted to use AI to ease the labor-intensive aspects of creating and analyzing a multimodal transcript; we aimed at reducing the time and effort needed for manual labeling of the dataset by training an AI to analyze video data for patterns of social interaction. Like Toivonen et al. (2019) suggested, the goal was not for AI to replace human analysis; rather, it was meant to augment it. Indeed, multimodal analysis needs human intervention so that the dynamicity of a phenomenon is not lost to the individual pieces. Thus, the AI-enhanced pattern recognition approach added a level of confidence to the study of children's CT by comparing and/or complementing the findings from the grounded approach and transduction. This provided us an insight into the phenomenon that would be difficult to achieve using human analysis alone.

Preliminary Results From the First Data Entry. After training the algorithm, we fed the AI with a 5-minute video segment to see how the AI performed and understand how the AI approached the emergent and self-organizing nature of children's CT. This 5-minute segment of the video was not part of the original video used to train the AI. Instead, we randomly selected a new segment and extracted 600 images from the 5-minute segment for analysis.

AI Performance. Table 4.7 displays an excerpt from the computer output (see Appendix C for the full output). The numbers in the output correspond with the label key associated with the analysis. For example, a result of 0.0 represented the absence of interaction, whereas a result of 1.0 pointed to the existence of interaction. Thus, the result of "0.0, 1.0, 0.0, 0.0, 1.0" for image '5-minute Trim0000.jpg' in the first row suggested that in the first image, the computer and workbook appeared simultaneously (marked 1.0) while numerical representation, imitating the robot, and robot itself were absent (marked 0.0). In cases where the result was neither 0.0 nor 1.0, the result was rounded to the nearest whole number (e.g., '5-Minute Trim0004.jpg').

Table 4.7

An Excerpt from The Computer Output

Video Name & Label Key: Numerical Representation, Computer, Imitating Robot, Robot, Workbook
['5-Minute Trim0000.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
['5-Minute Trim0002.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
['5-Minute Trim0003.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
['5-Minute Trim0003.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
['5-Minute Trim0004.jpg', 0.0, 1.0, 0.0, 0.0, 8.842248e-25, 1.0]

The output was then analyzed with a frequency count; this enabled us to determine what mode of interaction became more prevalent in a specific fragment of the data. In the 5-minute segment of video, the most frequent result was that of the participants working at the computer while also referencing their workbook (0.0, 1.0, 0.0, 0.0, 1.0); this occurred a total of 451 times. If the 5-minute segment resulted in 600 images, then a single image reflected 0.5 second of time. Thus, the students spent roughly 3.75 minutes (451 instances x 0.5 seconds, divided by 60) of the 5-minute segment working with the computer and workbook as a mode.

The next most prominent interaction was the participants working at the computer with no other modes present (0.0, 1.0, 0.0, 0.0 ,0.0) ; this occurred 116 times. Thus, the students spent roughly 0.98 minutes (118 instances x 0.5 seconds, divided by 60) of the 5-minute segment working at the computer with no other modes involved. The next most frequent result was of the participants holding the robot and referencing their workbook (0.0, 1.0, 0.0, 1.0, 1.0); this occurred 18 times. The students spent roughly 0.15 minutes (18 instances x 0.5 seconds, divided by 60) of the 5-minute segment holding the robot and referencing their workbook.

The only other arrangement identified by the AI was of the participants working at the computer while making a numerical representation while working with the workbook (1.0, 1.0, 0.0, 0.0, 1.0); this occurred 3 times. The students spent roughly 0.03 minutes (3 instances x 0.5 seconds, divided by 60) of the 5-minute segment working at the computer while making a numerical representation while working with the workbook. No other arrangements were identified by the AI. A visual inspection of the 5-minute video clip confirmed that these frequency counts largely reflected the modes of interaction present; the entire clip entailed the participants working to program the computer, drawing on different tools throughout the process (e.g., the robot, their workbook).

Emergence and Self-organization. Considering the findings above, it could be argued that the AI-pattern recognition tool was efficient in identifying the modes of interaction, and the frequency of these interactions in a specific time interval. With regard to self-organization and emergence, the AI-enhanced pattern recognition approach is remarkably similar to that of the grounded approach. Specifically, the results revealed the individual components of the system that were visible in our video clip and their frequency of interaction. For example, it was clear that the participants made extensive use of their workbooks as they worked to program the computer in this 5-minute video segment. What was missing, though, was an understanding of *how* and *why* one mode was selected over another by the participants. This is not surprising—as revealed in the case of transduction, above, one must consider what is happening *across modes,* including the dialogue, to fully understand the meaning behind those modes.

Overall, the results of the AI analysis are promising and have significant implications for further research. First of all, creating an output that indicates the frequency of interactions as part of a progressive timeline would indicate the shift across the modes, over time, within the categories initially identified. Likewise, spoken dialogue could be added to that timeline to enhance further a transduction approach. Second of all, if a researcher is particularly interested in a specific type of social interaction (e.g., most frequent; least frequent), that interaction could be easily elicited from the computer output for deeper analysis. Last but not least, AI-enhanced pattern recognition could be used to cross-check and validate the findings of other research methods that have previously relied on human input and the judgement of the researcher. This would add another layer of confidence to the research that would be difficult to achieve using human analysis alone.

Cross-unit Comparisons: The Affordances & Limitations

Within-unit analysis opened a discussion about the alignment of each approach to the characteristic features of a non-linear, complex system. Next, a cross-unit analysis was conducted to determine the affordances and limitations of each approach when used to reveal self-organizing and emergent nature of children's CT. The cross-unit analysis helped answer:

4. What are the key strengths and differences associated with the three different approaches to the multimodal analysis of children's CT?

This section will compare and contrast the key differences/strengths/weaknesses associated with three different approaches to multimodal analysis of children's computational thinking based on the lens of complex dynamical systems theory. An overview of the results of this analysis is presented in Table 4.8.

Table 4.8

The Summary of the Major Comparison Points

	Grounded Approach	**Transduction**	**AI Enhanced Pattern Recognition Tool**
Self-organization	<u>**Partial:**</u> Strong in Revealing The Modes of Interaction	<u>**Partial:**</u> Strong in Revealing the Shifts across Modes	<u>**Partial:**</u> Strong in Detecting Multimodal Interactions
Emergence	<u>**Partial:**</u> Strong in Revealing Agent-based Reasoning: Unit Movements	<u>**Partial:**</u> Strong in Combination of Agent-based and Aggregate Form of Reasoning: Multiplicative Reasoning	<u>**Partial:**</u> Strong in Detecting Multiple Interactions in a Single Frame

The account of grounded approach and transduction brought different strengths and weaknesses to the table to study the self-organizing and emergent nature of a complex system. For Nathan and Swart (2020), every complex system spontaneously develops sub-assemblies to adapt to ever-changing environmental conditions, aligning with the notion of survival of the fittest. This has one significant methodological implication; the study of a complex system starts from a comprehensive understanding of the emerging parts inside of that system. Nathan and Swart (2020) therefore suggest functional decomposition as a way of studying complex systems. This aspect of studying complex systems—that is, functional decomposition—appears to be something the grounded approach is well suited for. The results of the grounded approach helped reveal the specific components within the system and the function of those components. In the case of children's CT, this involved their own bodies as well as the tools in the environment (e.g., robot, workbook, computer).

The process of transduction, in contrast, was more sensitive to the "looseness into the human–environment coupling" (Abrahamson & Abdu, 2020, p. 16)—that is, the approach was more responsive to the emergent and self-organizing nature of CT as a complex system. One reason for this flexibility has to do with the purpose of transduction, which is the "remaking of meaning involving a move across modes" (Jewitt et al., 2016, p. 72). As an analytical approach, transduction specifically targets the interplay of semiotic resources that are used by the participants for meaning-making activity.

In this study, transduction revealed how CT emerged as the interaction between each participant's unique meaning-making activity and choice of modes. Transduction made transparent the ways in which the participants imitated the robot as they used proportional reasoning to decompose the overall task, then turned to the computer to program the robot's movements with greater mathematical precision (i.e., algorithmic thinking). This transparency was lacking with the grounded approach because the grounded approach was less equipped to reveal the spatial and temporal organization of the participant's embodied interactions. Because the process of transduction attended more fully to the interactions between and across modes, it was more responsive to the emergent nature of children's development of CT, resulting in findings that revealed the meaning behind the participants' shifts across the modes. This was likely enhanced by the use of various stylistic features in the transcript (e.g., right-facing arrow (→); bracketed descriptions of bodily movements), which also helped reveal the patterns that were unanticipated and, at time, seemingly disordered (e.g., multiplicative reasoning) in the data.

Even though the process of transduction was more sensitive to the "looseness into the human–environment coupling" (Abrahamson & Abdu, 2020, p.16), the grounded approach offered a good start to data analysis for educational complex systems. Multimodal researchers face a lot of challenges, particularly when dealing with large volumes of complex data (e.g., over 20 pages of a multimodal transcript) that involve the collective social behavior or embodied interactions. Integrating a scale-down methodology like the grounded approach broke the overall system down into its nearly decomposable parts (Bradshaw, 2005; Nathan & Swart, 2020). The findings from this study suggest how important the idea of CT as a *nearly* decomposable system is. CT is *nearly* decomposable because "fully decomposable systems are made up of modules that function independently and additively" that makes them essentially linear, and predictable (Nathan & Swart, 2020, p.16). The grounded approach proved to be a method that upheld the complexities inherent in CT while also providing a lens into the complexities of that system. At the same time, the grounded approach could only reveal a limited understanding of that complexity. While the grounded approach treated CT as nonlinear, unpredictable, and indeterministic (You, 1993; Jacobson et al. 2016; Nathan & Swart, 2020), it did not reveal any great insight into how the components of the complex system behaved *across* the system. Therefore, a grounded approach to analyzing a multimodal transcript can be considered an approach that reveals the complexity of children's computational thinking by identifying its nearly decomposable subsystems.

One significant finding from the grounded approach was the participants' incorporation of a set unit movements to control the robot. These findings from the grounded approach served the transduction process, which ultimately revealed how CT emerged—the unit movements preserved the proportional relationship between speed, time, and distance (Kopcha & Ocak, 2019; Kopcha et al., 2020). In particular, the participants' use of halves and doubles eventually emerged as a major tool that supported deliberate decomposition of a task to achieve the desired movement of the robot. This finding illustrates how a scale-down approach (i.e., grounded) can support a scale-up approach like transduction. Identifying the unit movements contributed to the researcher's identification of multiplicative reasoning at a broader scale to explain how the behavior of the overall system emerged and organized itself over time. In this way, the emergent nature of CT was revealed. The participants engaged in patterns that were seemingly disconnected from a scale-down perspective, but strongly connected from a scale-up perspective.

Bezemer's (2014) third step, *Design the Transcript*, played an important role in the findings. For example, transduction resulted in verbatim transcription of speech and short sequences of images used for the analysis of semantic context that framed the gesture. These were then summarized from the researcher's perspective in a third column. In contrast, the grounded approach provided an in-depth description of each tool (e.g., basic robot moves, gestures), and the ways in which participants acted upon these tools (see section 4.1), without emphasis on how those tools aligned with other modes, such as dialogue, at a given point in time. The attention to the temporal and spatial aspects of the participant's interactions in the transduction process ultimately aided data analysis and interpretation. The transduction column, in particular, helped reveal the self-organizing nature of the system through the behavioral patterns that emerged from participants' embodied interactions (Kopcha et al., 2020). A priori coding and thematic analysis of the multimodal transcript further aided this analysis, helping to reveal the relationship between the modes rather than focus on individual behaviors of the agents. Even though the grounded approach to analyzing the multimodal transcript was powerful in identifying the system's nearly decomposable components around the core variable, the transduction account provided a clearer depiction of the ways that CT emerged and organized as a complex, dynamic system.

Understanding how each approach supported the study of CT as a complex system is important in the field of learning, design, and technology. Jacobson et al. (2019) argued that quantitative and qualitative methodological approaches are limited in revealing these particular aspects. In their study, Jacobson et al. (2019) suggested certain computer modeling techniques agent-based models (ABMs), and equation-based models (EBMs) as a complementary addition to two major research paradigms: qualitative and quantitative approaches. ABMs and EBMs draw on two distinct types of reasoning. Similar to the idea of scale-up and scale-down perspective, ABMS uses a "bottom-up" technique to model the behavior of an agent at a certain level, while EBMs employ a "top-down" approach drawing on the algorithms modeling the overall behavior (p.115). In this study, the findings indicated that the grounded approach has been successful to identify agent-level interactions while the transduction approach provided macro-level analysis of the collective social behavior without the need of a computer modeling.

However, as a complementary addition, the AI-enhanced pattern recognition tool addressed the current issues of trustworthiness related to the merit and/or accuracy of the findings, through the cross-check with the other two methods to draw a more holistic account of participants' development of reasoning in the context of CT. Cross-checking has been particularly useful for some aspects of embodied interactions that could be easily missed or overlooked due to the labor-intensive work of creating a multimodal transcript, thinking that the average 5-minute video segment contains ~1,000 possible frames/images for analysis.

Yet still, the findings from the AI-enhanced pattern recognition tool offered only a partial insight into how CT developed as a function of embodied interactions. The output from the AI addressed two essential questions: what were the mode(s) of interaction preserved in a frame, and how did the(se) mode(s) of interaction evolve as the frames shifted. We used the primary modes of embodied interactions from the grounded approach to train the AI; the five major categories were (1) [the interaction with the] workbook, (2) [the interaction with the] robot, (3) imitating the robot, (4) [the interaction with the] computer, (5) numerical representation. These categories helped to successfully train the AI (i.e., 80 % percent) to detect the modes of interaction that the children were involved with in a moment-by-moment fashion. Therefore, the grounded approach and the AI-enhanced pattern recognition tool were complementary in that the grounded approach broke the overall system into the major modes of interactions and the AI helped to classify these interactions under these nodes. What was missing from both approaches, once again, was the overall reasoning behind the learner's preference of one mode to another, over time, which was to be further interpreted by researchers through transduction. Overall, it can be drawn as a conclusion that each method mutually advanced one another in a complementary fashion.

To sum up, learning is a self-organizing system, which means CT is also self-organizing (You, 1993). Learners are constantly prompted to self-organize when discrepancy between their prior and new knowledge emerges, or when a predicted outcome fails to emerge. This is simply reflective of the adaptive nature of learning. As You (1993) explained, "new knowledge destabilizes the learning process, thus necessitating reorganization and restabilization" (p.24). In the context of CT, this destabilization manifested itself through participants' shifts across the modes, as articulated in the process of transduction. The shifts across the modes originated from the participants' "cognitive dissonance" (You, 1993); when one mode of expression did not meet the participants' source goal, it either had to be diminished or complemented with the other modes.

The findings from each analytical approach provided an abundance of evidence about how and why of participants' move-across the modes. In one of the scenes of the multimodal transcript, the participants observed that the unit movement did not move the robot in the right amount; therefore, it had to be tailored. The discrepancy that arose from the misalignment between what the participants initially planned and what they accomplished resulted in the conceptualization of possible solutions such as *going faster* or *a small increase* in the distance the robot travels. The transduction process more efficiently attended the moments of discrepancy that were revealed through the shifts across the modes. When coupled with in-depth understanding of the modes in the data, transduction helped draw more comprehensive conclusions of the data—by revealing *why* they made their choices. The findings from the grounded approach and transduction therefore supported that both methodological tools were responsive to the dynamic nature of CT; the AI-enhanced pattern recognition tool added a level of confidence while studying the complexity in the context of CT.

CHAPTER 5

Conclusion

This dissertation addressed *how researchers can study CT in a way that upholds the complexity of the system*. In this context, this study offered three major analytical techniques, each of which was aligned with studying CT as a dynamical system. The findings indicated that each layer was complementary to each other rather than competitive in revealing the major characteristic features of the complex systems such as self-organization and emergence. Whereas the grounded approach helped explore the individual components in the system through the various modes of meaning-making, the transduction supported understanding the interplay of these components through various shifts in modes. The AI pattern-recognition approach increased the level of confidence in the findings from the merit and/or accuracy of transcripts through the guide of what part of human-tool interaction becomes more relevant in a specific fragment of the video.

This study also aimed at contributing to a crucial gap in the literature underscored by Jacobson et al. (2019)—how existing education research has remained insufficient in addressing two major key features of complex systems: non-linearity and emergence. To fill in this gap, I first created a conceptual framework that conceptualizes CT as a complex dynamical system. Next, drawing on these concepts, a combination of methodological tools offered to study the non-linear and emergent nature of CT. This contributed to the understanding of the implications of dynamical systems theory and its methodological tools in education research.

Implications for Research

Several methodological implications are worth noting. First of all, the traditional positivist approaches may not fully attend to the dynamic and nonlinear nature of learning processes. As the findings suggest, this is because the participants adapted to the changing conditions of a system's surroundings. As do many others (Bereiter & Scardamalia 2005; Jacobson et al., 2016; Jacobson et al., 2020; Nathan & Swart, 2020), I echo the recurring need for education research that treats learning as a dynamical, and nonlinear that evolves as a result of ongoing interactions with the environment. Future research therefore should focus on children's embodied interactions and embrace the insight into the nature of CT would come more from *the way in which the components in the system interact with each other,* and how this interaction shifts *over time.*

Another major implication is that the boundaries between self-organization and emergence are not distinctive, but rather transformative. In other words, one is not a precursor to the other, rather each is related to and enhances the other. Therefore, research using multimodal transcription may benefit from combining scale-up and scale-down approaches to study the transformative characteristics of human learning, where scale-down is for the micro-analysis of the parts' interactions and scale-up to cover across interactions that reveal the emergent nature of collective social behavior at large (Nathan & Swart, 2020; Stein, 2007). This invites other researchers to embrace a variety of methodological tools that might involve either qualitative or quantitative and/or computer aided analysis.

For scholars interested in studying the CT as a dynamical system, this dissertation offers a powerful methodological framework. Near-decomposability and/or functional decomposition offers a powerful start to study the complexities of cognition (Nathan & Swart, 2020). Drawing on the techniques from a grounded approach, CT's homogeneous and heterogeneous components that involved human and non-human aspects of interaction were identified. The social semiotic approach multimodality helped study both agent- and system-level interactions as a function of modes for the multimodal data analysis (Dicks et el., 2011). In consideration of future implications, these methods are not a recipe for researchers to study complex system's phenomenon; rather a recommendation that reflects our underlying theoretical and philosophical approach towards studying the dynamicity of learning in the context of CT.

At the same time, one recurring challenge that the researchers face is to indicate the dynamicity in the multimodal transcript so that it could aid the analysis of self-organization and emergence (Bezemer, 2014). The way that we constructed the multimodal transcript was already a purposive endeavor to offer a design template that preserves the complexity of the participants' interactions. Additionally, the findings surprisingly indicated that the use of transcript conventions, combined with the side-by-side organization of *the dialogue, embodied interactions, and transduction,* could be used as significant tools to study the self-organizing and emergent nature of a complex system. Preserving sequences of images (i.e., embodied interactions) alongside the transduction column helped understanding the emergent reasoning of how participants' moved across different modes of meaning making. For example, the consecutive images helped constitute an implied timeline that indicated participants' shift across the modes—as displayed in brackets—by indicating their momentary preferences of one mode to another. Thus, the use of transcription conventions in the multimodal transcript not only helps to preserve the complexity of video data, but also helps guide researchers to study self-organization and emergence throughout the analysis. The general implication is that researchers need to consider representational choices as a contributing factor to the analysis of self-organization and emergence.

Implications for Practice

Last but not least, the AI-enhanced pattern recognition tool provided a new methodological tool for advancing our understanding of complex dynamical systems. The preliminary results have been promising—for providing an 80% accuracy in identifying the human-computer interaction, human-tool interaction, and human-human interaction. For the future research, an updated version of the AI could easily serve as proof of evidence to triangulate the findings from human analysis.

With a successful AI model in place, however, the researcher can repeatedly scan video data using whatever code type(s) helps answer the researcher's questions. As deeper insight is gained, a researcher can continue training the AI in new ways so that greater amounts of data can be analyzed more quickly. Comparing and/or complementing the AI analysis with human analysis brings a level of confidence to the research that was previously absent and difficult to achieve. This can provide the researcher with invaluable insight into the phenomenon that would be difficult to achieve using human analysis alone.

At the same time, even though multimodal transcription of video data offers a powerful way to research embodied thinking, video analysis is an overwhelming and daunting task for containing hundreds of potential images for coding and analysis. For future research, any AI output that indicates the frequency of interactions would drastically reduce the time and effort needed for manual labeling for the dataset.

Additionally, the technology-driven, AI-enhanced approach to analyzing computational thinking went beyond the current, often reductive methods. In the next step, the AI-enhanced pattern recognition tool could be designed to produce frequency tables and bar charts that situate the frequency of interactions in a progressive timeline. Through the display of relative frequencies, shift across the modes in the designated categories could be easily interpreted by the researchers. In this way, AI would help establish the behavioral indicators of computational thinking that may be missed or overlooked through traditional pre-post test methods, offering new possibilities for integrating, assessing, and studying computer science in K-12 settings.

Limitations

Jacobson (2020) critiqued qualitative approaches to studying educational complex systems for offering limited opportunities to detect the emerging behavior; rather, they are useful in providing thick descriptions of "what has already emerged" (Jacobson, 2020, p.378). The methods adopted in this study indeed do offer strategies to study what has already emerged. However, for the sake of this study, it has more value of offering tools to dissect/intextualize the data to develop an intuition about the possible motives that led to emergent behavior (i.e., development of CT), and offer an alternative method(s) to study complex learning systems from an embodied perspective.

Another limitation would be related to the one that involves the AI-enhanced pattern recognition tool. On one hand, the findings were indicative of how the tool would facilitate the design and creation phase of the multimodal transcript—this is a significant part of the data analysis process in multimodal research (Baldry & Thibault, 2005; Helm & Dooly, 2017). At the same time, the results suggest that AI cannot fully replace human analysis at this time. With any approach to analysis from a multimodal perspective, a researcher needs to look at the data and interpret the meaning behind the various modes of interaction. Thus, a researcher's presence is still very much needed in the case of AI-enhanced analysis. Rather than integrating solely computer models to study complex systems, the validation of computer outputs is needed through the comparisons of findings drawing on different methodological tools.

Even though AI eased the labor-intensive aspects of creating and analyzing a multimodal transcript, the time and effort still needed for manual labeling of the dataset by training an AI to analyze video data for patterns of social interaction. A researcher should carefully review and select images that best reveal the meaning behind one's embodied interactions (Bezemer, 2014; Bezemer & Mavers, 2011). This has been the biggest challenge that the research team has faced. Thus, researchers should be conscious of the fact that some instances of embodied interactions could easily go unnoticed. Additionally, the elimination of certain images to represent the best case might require some reduction in the dataset. Even though these challenges are inevitable, it is significant to report the reduction criteria—as was the case for this study (i.e., the criteria for selecting modes for manual labeling).

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APPENDICES

Appendix A

Technical Report of the Network Design

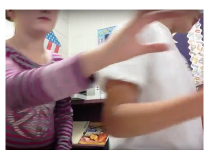
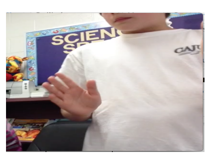
(R. Dey, personal communication, September 17, 2020)

The Software: Keras with Tensorflow Backend

The Network Design: The network consists of two convolution layers of thirty-two nodes, each followed by a dense layer of 5 nodes signifying the five possible classes. The loss function is binary cross-entropy. The optimizer is Adam, with a learning rate of 5E-5. The network prolyl uses face orientation to determine if a participant looks at a certain object. The network learns hierarchically; the first few layers detect edges while the deeper layers of the network hierarchically build up to more comprehensive features.

Appendix B

Addressing the Complexity that Emerges From the Environmental Coupling

Dialogue	**Embodied Interaction**	**Function of Embodied Interaction**
B: Now you need to make it turn!	 [He turns his whole body 270° spin]	[→ from decomposition] The pair continues to decompose and plan the next set of movements. The boy conceptualizes the turn that the robot will take. The boy turns his body two hundred and seventy-degrees while holding the robot in his hands as he spins to anticipate and demonstrate the outcome of the robot's turning.
B: Make it turn left! G: [Smiling] Stop [taking robot from B]! You are not the robot!	 [She reaches for the robot]	[→ to decomposition] The girl reaches for the robot as the boy turns away from her. She recognizes that the boy sees himself as if he is the robot. His movement is the same as the robot's movement, and, in particular, the wheels of the robot. This suggests how he embodies the constraints of the robot in his own thinking.
B: You have to make it do...speed four… backward.	 [He moves right hand forward, left backward at the same time]	[→ from algorithmic thinking] The boy then uses algorithmic thinking to articulate a speed setting while he uses his hands to indicate a left turn by moving the right hand forward and left hand backward simultaneously. The scene indicates that the boy still sees himself as if he

		were the robot while deciding the next move of the robot. He is coupled with the environment (e.g., the robot), and the coupling is enacted through the boy's gesture.
B: You have to make it do...speed four… backward.	 [She mimics robot movement from the program on the screen, pointing forward]	[→ to decomposition] The pair then keeps decomposing the next few steps of the task. The girl holds her hands like the wheels of the robot and moves backward. The boy then confirms her thinking, turning his body while moving backward. The scene indicates that the pair is coupled with the tools to orient the robot and anticipate the next movements.

Appendix C

Full Output from the AI that Indicates the Frequency of Interactions

	Video Name & Label Key: [Numerical Representation, Computer, Imitating Robot, Robot, Workbook]
1.	['5-Minute Trim0000.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
2.	['5-Minute Trim0001.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
3.	['5-Minute Trim0002.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
4.	['5-Minute Trim0003.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
5.	['5-Minute Trim0004.jpg', 0.0, 1.0, 0.0, 0.0 8.842248e-25, 1.0]
6.	['5-Minute Trim0005.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
7.	['5-Minute Trim0006.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
8.	['5-Minute Trim0007.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
9.	['5-Minute Trim0008.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
10.	['5-Minute Trim0009.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
11.	['5-Minute Trim0010.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
12.	['5-Minute Trim0011.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
13.	['5-Minute Trim0012.jpg', 0.0, 1.0, 0.0, 1.0, 1.0]
14.	['5-Minute Trim0013.jpg', 0.0, 1.0, 0.0, 0.0 2.4390392e-05, 1.0]
15.	['5-Minute Trim0014.jpg', 0.0, 1.0, 0.0, 0.0 2.6689117e-05, 1.0]
16.	['5-Minute Trim0015.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
17.	['5-Minute Trim0016.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
18.	['5-Minute Trim0017.jpg', 0.0, 1.0, 0.0, 0.0, 0.0]
19.	['5-Minute Trim0018.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
20.	['5-Minute Trim0019.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
21.	['5-Minute Trim0020.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
22.	['5-Minute Trim0021.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
23.	['5-Minute Trim0022.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
24.	['5-Minute Trim0023.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
25.	['5-Minute Trim0024.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
26.	['5-Minute Trim0025.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
27.	['5-Minute Trim0026.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
28.	['5-Minute Trim0027.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
29.	['5-Minute Trim0028.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
30.	['5-Minute Trim0029.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
31.	['5-Minute Trim0030.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
32.	['5-Minute Trim0031.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]

33.	['5-Minute Trim0032.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
34.	['5-Minute Trim0033.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
35.	['5-Minute Trim0034.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
36.	['5-Minute Trim0035.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
37.	['5-Minute Trim0036.jpg', 0.0, 1.0, 0.0, 0.0, 1.0]
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