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Research Article

Predicting Computational Thinking in Elementary Science Lessons Using a Multilevel Model Approach

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Computational thinking (CT) is an essential problem-solving skill that students need to successfully live and work with developing technologies. There is an increasing call in the literature by researchers and policy leaders to integrate CT at the elementary level into core subjects to provide early and equitable access for all students. While some critics may claim the concepts and skills of CT are developmentally advanced for elementary age students, subjects such as science can provide real-world and relevant problems to which foundational CT components can be applied. By assessing how CT concepts and approaches integrate authentically into current science lessons, policymakers, and district leaders can be more intentional in supporting implementation efforts. This research used an exploratory survey design to examine the frequencies of CT concepts (decomposition, algorithms, abstraction, and pattern recognition) and approaches (tinkering, creating, debugging, perseverance, and collaboration) that exist in science in K–5 schools in a northeast state in the United States as reported by elementary science teachers ($n = 259$). Hierarchical linear modeling was used to analyze the influence of teacher and district factors on the amount of time CT concepts and approaches were integrated in the science lessons. Experience, grade level, confidence, and participation in a research–practice partnership were found to be significant predictors of CT. This study contributes to a better understanding of variables affecting CT teaching frequency that can be leveraged to impact reform efforts supporting CT integration in science.

1. Introduction

Teaching and learning in a rapidly changing society where technology is ubiquitous poses many challenges in education. As computers become more pervasive in young children's everyday life, schools need to reassess the delivery of science, technology, engineering, and math (STEM) education to include computational thinking (CT). There is a need to increase access to computer science subject matter by concentrating on CT in schools; not only does it address workforce skills needed in the digital age, but learning the components of CT can provide a foundation for developing critical thinking and data analysis skills [1–3]. Increasing access to computer science by teaching CT to all elementary children will provide more opportunities for underrepresented groups and students from urban, rural, and low-socioeconomic areas to participate in this rapidly expanding field [4].

CT is a key element of computer science. In 2006, Wing [5] introduced this process in her seminal paper in which she described CT as "a fundamental skill for everyone, not just for computer scientists. To reading, writing, and arithmetic, we should add CT to every child's analytic ability" [5, p. 33]. There are many definitions for this term and its component parts found throughout the literature, which has caused challenges in communication between policymakers and practitioners [5–12]. However, just like Wing indicated in her definition, other definitions support the idea of CT being a foundational skill that all children should learn. The following definition guided the researchers of this project to better understand CT experiences at the elementary level.

> "A problem-solving process that includes a number of characteristics and dispositions. CT is essential to the development of computer applications, but it can also be used to support problem-solving across all disciplines, including the humanities, math, and science. Students who learn CT across the curriculum can begin to see a relationship

The definitions for the CT concepts [17]

Algorithm:	"a set of rules to get something done"
Decomposition:	"breaking down a task into smaller more manageable parts"
Patterns:	"spotting similarities and differences"
Abstraction:	"identifying what's important without worrying too much about detail"

The definitions for the CT approaches [17]

Tinkering:	"explore and experiment to try things out"
Creating:	"plan and make things"
Debugging:	"find and fix errors through predicting what should happen, find out exactly what did happen, work out where something went wrong"
Persevering:	"be determined, resilient, and tenacious"
Collaborating:	"work with others to ensure the best results"

Figure 1: Definitions for CT.

> between academic subjects, as well as between life inside and outside of the classroom." [13, p.1].

> "Computational thinking allows us to take a complex problem, understand what the problem is and develop possible solutions. We can present these solutions in a way that a computer, a human, or both, can understand." [14]

The characteristics, which form the core concepts of CT, consist of *creating algorithms*, *using abstraction*, *using decomposition*, and *recognizing patterns*. The dispositions, which provide approaches for engaging in CT, consist of tinkering, creating, debugging, persevering, and collaborating [15, 16]. Figure 1 shows the definitions of the CT concepts (characteristics) and approaches (dispositions) examined in this paper [17].

These concepts and approaches are from a framework created by Computing [17] at Schools (CAS), an organization from the United Kingdom that has been a leader in supporting computer science education in schools since 2008. A design-based implementation research (DBIR) team composed of 25 participants with various expertise and current job titles including elementary math and science coaches, K–5 teachers, district curriculum coordinators, and university educators across STEM plus computer science content, chose this framework after a rigorous process of conducting a literature review and crosswalking of state, national, and international standards. The research team chose the CAS components for CT because the language was easy to understand and provided clear guidance for teachers who may not be familiar with CT. The concepts (algorithms, pattern recognition, abstraction, and decomposition) also utilize the same terminology as the International Society for Technology in Education (ISTE). These concepts and approaches provide a shared language and foundation for integrating CT into core subject disciplines, like science, which is essential to the development of computer applications which allows students to see a relationship between the different subjects [16, 17]. While the CT concepts and approaches described in this paper may not be unique to CT which lays foundations for computer science, they are digestible for elementary teachers because of the versatility of the terms. The real work comes with making these terms more explicitly connected to the work of computer science professionals.

Exposing children to CT at an early age has been shown to motivate them to develop computer science skills [18–21]. However, for early experiences with CT to have positive impacts on future learning, school systems need resources to effectively integrate the concepts and approaches into their epistemology, content, pedagogy, and practice [22]. Curriculum efforts have not been spread school-wide nor have best practices been established to educate teachers on how to integrate effectively [23]. In addition, systematic research is needed before large-scale implementation can take place and be sustainable.

The purpose of this exploratory study is twofold: first to examine the frequency of CT concepts and approaches currently taught in elementary science classrooms; second, based on ecological perspectives [24], to explore the extent to which teacher factors (grade level, teaching experience, professional development, confidence, and level of concern) and district-level factors (classification, socioeconomic status (SES), and science curriculum) affect CT frequency levels. This study builds on the foundation for research and implementation of CT integration into science by addressing the following research questions:

RQ1: How often are CT concepts and approaches currently taught in K–5 science classrooms?

RQ2: To what extent are teacher characteristics (grade level, teaching experience, professional development, confidence, and level of concern for implementing CT) and district contexts and policies (district classification, SES, and science curriculum) related to the frequency of teaching CT concepts and approaches in K–5 science classrooms?

2. Literature Review

2.1. CT in Elementary Science. The goal to integrate CT into elementary science instruction is supported by research and policy, yet barriers prevent the type of instruction needed to make this a reality. Although CT can be taught as a standalone subject, it is best learned when embedded in class subjects such as science and taught in context using an interdisciplinary approach [25]. When CT is integrated into required core subjects, it is more likely to reach all children, allowing for a more diverse population to develop an interest in and pursue STEM and computing careers [26]. Weintrop et al. [27] contend that "science and mathematics are meaningful contexts in which we can successfully situate the concepts and practices of computational thinking" (p.128) and address the issue of reaching all students by occurring in a core discipline. They created a taxonomy for integrating CT into science instruction that consists of data practices, modeling and simulation, computational problem solving, and systems thinking [27].

Past initiatives in computer science have paid more attention to addressing the college and secondary levels rather than the elementary level [28–33]. However, efforts and attention are now being focused on the teaching and learning of CT in elementary classrooms [12, 34]. The rationale for integrating CT at the elementary level is to introduce key concepts and experiences to children at an early age to develop positive attitudes toward disciplines; it has influence in career choice and allows more access to foundational skills and higher paying jobs [33, 35, 36]. Engaging in CT involves complex systems thinking that takes time to develop but can be broken into manageable concepts and approaches for students to acquire overtime. Foundational CT concepts and approaches have been successfully taught to children as young as four [20, 37]. As found with many educational innovations, interventions that begin early have stronger positive outcomes than the interventions that start later [38, 39].

There are some systems in place that may help with the integration of CT in science content. For example, most states in the United States of America, including the northeast state in this research study, have adopted the Next Generation Science Standards that were developed in 2013. These science standards include CT as one of the eight engineering practices [9]. However, when viewing the disciplinary core ideas of the NGSS, the opportunities for CT at the elementary level in science content instruction are limited as opposed to the secondary level. Countries across the globe indicate CT is a relevant skill set all students should engage in and have established frameworks like the NGSS, but with diverse terminology and varying implementation efforts [22, 32, 40, 41]. The ISTE have identified the skills, mindsets, and knowledge that practitioners can use to integrate CT across K–12 content areas with students of different ages [16]. These frameworks can be built upon to make CT at the elementary level more universal and widespread.

2.2. Implementation Challenges. School systems are facing challenges in implementing CT in elementary science instruction. A lack of teachers available with computational skills, the shortage of funds to hire qualified teachers and purchase CT materials, the prioritization of instructional time devoted to mandatory testing subject like math and ELA, the limited time for planning CT-infused lessons, and the overwhelming nature of CT integration especially when teachers are not confident, knowledgeable, or experienced with science or CT, are just a few of the implementation challenges [29, 42–44]. In addition, teaching science can sometimes be a challenge for elementary teachers because they lack the pedagogical knowledge and experience necessary to teach children scientific concepts and practices confidently. Elementary teachers are often generalists who are responsible for teaching and keeping up with the latest content in a multitude of subject areas. Furthermore, educators need to teach different scientific disciplines such as life, earth and space, and physical science utilizing reform-based scientific practices [45]. In addition, administrators and district leaders need support to help teachers implement science and CT content successfully.

The number of years of teaching experience varies greatly among elementary teachers which also can influence implementation. More experienced teachers often promote higher order thinking which leads to advances in critical thinking [46]. This is the kind of skill set needed by all teachers when implementing CT. In addition, the amount of time devoted to science instruction varies too. Curran Kitchin J [47] analyzed data from the early longitudinal childhood study and found more time teaching science increases academic achievement in science because it provides more opportunities to learn. However, the amount of time spent on science instruction can be dismally low at the elementary level. Since time available to teach science varies, implementation efforts prioritizing what is important for students to learn is something districts need to reflect on constantly with our rapidly changing world.

Other challenges with implementation include the need to increase awareness of CT, develop shared language, build leadership, and have professional development opportunities on how to integrate CT. It is particularly challenging for school leaders to support teachers because not all educators share the same definition for CT, and there is no clear-cut way for CT to be positioned in the curriculum. It needs to be understood that CT is not just a skill set that can be used for a lesson here or there but something that may be woven into multiple lessons [25]. To form a shared understanding, information must be collected on what researchers, practitioners, and policymakers are envisioning for CT at the elementary level. There is a need to figure out how to place CT in an already overburdened curriculum, consider what is developmentally appropriate for the different grade levels and how it applies in various contexts. A systematic rollout should be considered for teacher professional development and suitable student assessments. In last, CT integration will require effective communication and continued support for the educators [22].

2.3. CT Curriculum. Both computer-based (building-block programing, tangible programing, digital game creation, and robotics) and unplugged programs exist to teach CT at the elementary level [48]. Unplugged activities do not use a computer; instead, teachers use curricula such as Thinkersmith, Code.org, and CS unplugged [49]. Many of these programs are taught as stand-alone instruction accessed by some students; however, more emphasis is now being placed on programs and curricula that integrate into core subjects that can be easily accessed by all students. Examples of CT integrated into the science curriculum are becoming more prevalent. Bers [37] created models where concepts of CT are integrated into core subjects with children as young as four using a tangible program called KIBO. It utilizes open-ended activities and an approach, referred to as a "playground," to create sequences or algorithms [37]. Sengupta et al. [50] used CT in Simulation and Modeling (CTSiM) to teach science lessons using decomposition and abstraction and found significant learning gains between pre- and posttests. Waterman et al. [51] provided a framework for taking existing science lessons and enhancing and extending them using CT to support science learning. These are examples of curricula that embedded some of the CT concepts and approaches in science lessons, indicating opportunities for integration.

2.4. Teacher Development. Designing professional development for preservice and in-service teachers is essential for CT implementation [12, 34, 52]. Factors that impact the effectiveness of the professional development include the concern or buy-in of the teachers regarding implementation, the location of the school and grade level being taught, student demographics, and the confidence or self-efficacy of the teacher with computer science innovations. Hall and Hord [53] believe when starting the implementation process, it is best to determine the teachers' level of concern and address their concerns through various methods such as coaching, mentoring, or explaining in more detail the importance of the change.

District location (such as urban or rural) and grade level also play a role in teachers' motivation, students' physical skills, and users' access to CT [54]. In addition, teachers educating students in less affluent districts might need additional support. Karpinski et al. [35] reported data from the 2018 International Computer and Information Literacy Study indicating students from less advantaged backgrounds have lower levels of CT skills than those from more advantaged backgrounds. Therefore, designing effective CT professional development to address this inequity is necessary. Research has also indicated professional development in CT helps build teachers' self-efficacy when integrating it into their teaching [55, 56]. The thoughtful design of professional development using modeling experiences helps to increase teachers' confidence or self-efficacy by allowing teachers to believe in their ability to complete a task which gives them the confidence and skills to do it [57]. Factors that contribute to being a confident science teacher include\a strong science background, the desire to implement reform-based practices, and experience teaching elementary science [58].

2.5. Research–Practice Partnerships (RPPs). RPPs are a viable strategy for integrating CT in the science classroom where both researchers and practitioners benefit from the partnership. When school districts belong to an RPP, teachers are more likely to receive research-based curricula and pedagogy support [59]. RPPs are characterized as long-term collaborations between researchers and educators focused on continuous improvement and paying close attention to solving problems of practice [60]. RPPs benefit both researchers and practitioners because the relationships develop shared knowledge. Researchers can evaluate and develop instructional activities that are more easily translated into classroom practice. At the same time, practitioners can be provided opportunities to investigate problems of interest to them and feel supported while taking risks in the classroom. RPPs provide opportunities for new voices, questions, and observations when conducting research [61, 62]. Cadieux Boulden et al. [63] experienced some success integrating CT into a middle school science classroom while being part of an RPP. They found that best practice consisted of finding teachers willing to engage in the process and take risks. At the same time, having researchers who are flexible with school schedules, meeting teachers at their comfort level and making frequent visits to the classroom for support is also helpful. They also suggested that both researchers and practitioners need to engage in timely and thoughtful communication to successfully integrate CT [63]. Research has clearly shown progress is being made in integrating CT in science. These studies provide a foundation for further research to respond to the growing need for students to gain CT skills and concepts at the elementary level. This research aimed to find out the different ecological system factors that affect the learning and development for successful CT integration and implementation.

3. Theoretical Framework

This study adopts the ecological systems theory to support the multilevel modeling research design and the complex systems that impact curricular decisions of a teacher and district. The theory demonstrates the complexity with four layers, the microsystem, the mesosystem, the exosystem, and the macrosystem, that influence the learners directly and indirectly. The microsystem incorporates people who directly influence the child, such as teachers and parents. The mesosystem consists of the relationships among different structures in the microsystem such as interactions with parents, teachers, peers and how they affect the child. The next layer is the exosystem, the indirect environment that can influence the child's development, such as district-level personnel who make curricular decisions. The outermost layer, the macrosystem, includes social and cultural values that influence the inner layer systems, such as SES, ethnicity, and poverty. Figure 2 provides a diagram of the layers in Bronfenbrenner's ecological model [64].

Although all layers of the system could influence the integration of CT in the science curriculum, this study examines the microsystem and exosystem that exist in this multilayer context. The microsystem, or the qualities of the teacher that directly influence the students, will be examined

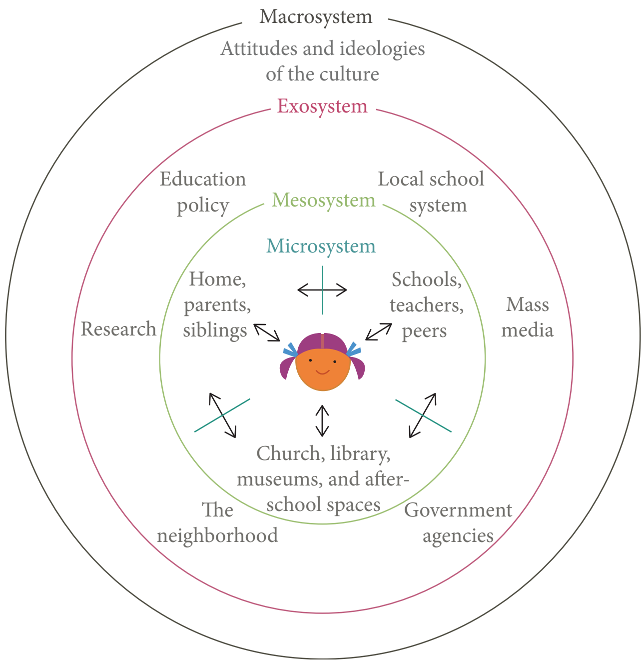

Figure 2: Ecological model.

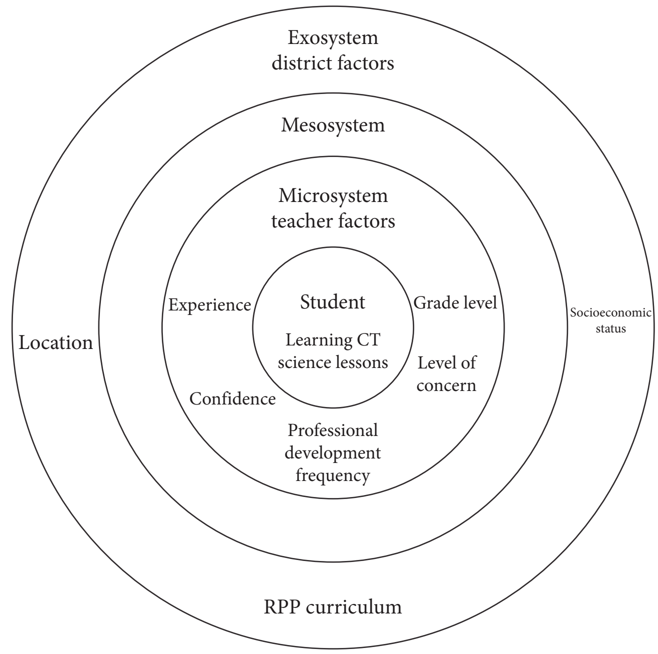

Figure 3: Ecological model of factors researched on CT integration in science lessons.

to determine if variables such as experience, confidence, grade level, or level of concern affect the teaching of CT. The exosystem, or the indirect environment, will be examined to determine if contextual variables such as location (rural, suburban, and urban), SES, and district-level curricula policies impact the use of CT in the science classroom as modeled in Figure 3.

In this study, district contexts and policies were selected as predictors for the exosystem layer as they influence teacher perceptions and behaviors, especially the participation in an RPP which is decided at the district level. Although this study does not include all four levels of ecological systems theory, it recognizes the multilevel characteristics of nested data (teachers are nested within districts) by utilizing a multilevel analytic tool, hierarchical linear modeling (HLM). A few recent studies have looked at these variables independently. In a small-scale study, Kale et al. [54] found teachers in rural settings had significantly lower CT skills than teachers in urban environments. Karpinski et al. [35] found that students from less advantaged backgrounds have fewer CT skills than students from more advantaged backgrounds. District-level curricula decisions such as belonging to an RPP have also been found to impact CT skills in the classroom [63]. This study fills a gap in the literature by analyzing large scale quantitative data with multilevel modeling that allows researchers to examine the effects of both teacher characteristics and district-level policy and context. Research has shown that explicit modeling of nested data structure would provide more accurate estimates of the cross-level inferences [65].

4. Methods

4.1. Participants. Elementary school teachers in grades K–5 in a northeast state were invited to participate in the CT survey as part of the larger STEM + C research study which investigated how teachers perceived CT within their current lessons across the core domains of math, science, social studies, and ELA. After IRB approval from the university was obtained, the teachers were invited directly via emails obtained from school websites and through contact with their superintendents and principals via emails and written mailed letters using contacts provided by the Department of Education database. The total number of elementary teachers who took the survey was 560, with a response rate of 12% of the state's teacher population. Of the 560 teachers who responded, 259 teachers from 30 different districts taught science. The achieved sample included only the teachers who took the survey and taught science: 94.2% females, 94.6% White/Caucasian, and 77.7% having over 10 years of teaching experience. The teachers ranged from only having 1 year of teaching experience to over 20 years of experience with a mean being 16 years of experience. These findings are similar to the demographics of the population of elementary teachers who participated in the National Survey of Science and Mathematics Education Survey (NSSME+) [66]. The grade levels taught by the teachers who took the survey were similarly represented from the kindergarten to fifth grade.

There are 185 elementary schools in this northeast state with 62,499 students and ~4,500 teachers. The overall demographics of students being taught by these teachers are 8% African American, 3% Asian, 25% Hispanic, 4% Multiracial, 1% Native American, and 59% White. Of this population, 47.5% of the students are eligible for subsidized lunch, and 15% of the population receives special education services [67].

4.2. Instrument and Variables. The CT survey was created by the university researchers using the tailored design method [68]. The CT survey was examined for face, construct, and

Table 1: CT concepts and approaches definitions and examples.

CT concepts and approaches	Definition and example at elementary level modified from barefoot computing at school [19]
Decomposition	"Process of breaking down a task into smaller, more manageable parts" example: planning a research project or labeling a life cycle
Patterns	"Spotting similarities or common differences" example: see similarities and differences in data collected
Abstraction	"Identifying what is important without worrying too much about detail" example: making notes or charts of the most important information
Algorithm	"Find and fix errors through predicting what should happen, find out exactly what did happen, work out where something went wrong" Example: How to get dressed or brush their teeth
Creating	"Planning and making things" example: making models
Persevering	"Be determined, resilient, and tenacious" example: tackling difficult problems while experiencing confusion
Tinkering	"Explore and experiment to try things out" example: figuring out how things work
Debugging	"Finding and fixing errors" example: fixing errors in their work
Collaborating	"Work with others to ensure the best result" example: working as a team

content validity by a DBIR group composed of 25 professionals: elementary science and math coaches, elementary teachers, district curriculum coordinators, and university educators with STEM + C backgrounds. After a pilot study of 125 elementary teachers, a test–retest procedure using Spearman's rank-order correlation was implemented to determine reliability of the survey questions which was found to be statistically significant ($\rangle = 0.840$, $p < .01$) [69]. Minor changes were made to improve the questions, format, and frequency scales by the DBIR team after discussing the survey. The revised survey was conducted in the academic year of 2019–2020.

The survey contained 55 questions and took teachers ~30 min to complete. The web-based survey questions included the frequencies of each concept and approach integrated into the science lessons. The survey was educative in describing the concepts (decomposition, abstraction, pattern recognition, and algorithm) and approaches (perseverance, creativity, tinkering, debugging, and collaboration) involved in CT. To establish a mutual understanding of these concepts and approaches across teachers, they were described in the same type of structure with a definition, examples, and a picture described by Barefoot Computing at school curriculum (see a table showing a description and example of each concept and approach in Table 1. The appendix is a copy of the survey given to the elementary teachers).

The dependent variables in this study are the frequencies (average minutes) of CT concepts and approaches taught in science classes. The variables were calculated based on two questions: total minutes per week teachers report teaching science and the total percentage of time teachers are engaged in the teaching and learning of CT concepts and approaches throughout the school year.

Independent variables were various teacher-level and district-level factors. Teacher characteristics include K–5 grade level taught (GRADE), years of teaching experience (YRSEXP), and the amount of time spent engaging in computer science professional development (PDHRS). In addition, the level of confidence teaching CT (CONFID) was measured on a 5-level Likert scale ranging from "not at all confident" to "extremely confident." The level of concern for implementing CT (CONCERN) was measured at seven stages about implementing CT into their lessons based on the stages of concerns based adoption model [70]. District characteristics include the district location (LOCATION—urban, urban ring, suburban, and rural) and SES as the percentage of families in the district below the poverty level (National Center for Education Statistics, n.d.). The type of curriculum used in the district (Stemscopes, Gizmos, Kit-based, Make My Own, and GEMS-NET) was another variable of interest in the study. The GEMS-Net curriculum is part of an RPP that uses FOSS kit-based materials and has ongoing progressive and mandatory professional development on research-based pedagogies. Belonging to an RPP is a critical component that differentiates the GEMS-Net curriculum from any other kit-based curriculum. As the emerging literature demonstrates promising insights for using an RPP framework when integrating CT [63], this study used a dichotomous variable (RPP) indicating whether the district participates in an RPP or not.

4.3. Data Analysis. Based on the ecological model [24], this study used a multilevel model that examined how the teacher-level and district-level factors are related to the integration of CT concepts and approaches into science instruction. Most of the current research on the integration of CT in science is exploratory and qualitative [32]. Moreover, a larger ecological system such as district contexts and policies were rarely examined with the consideration of the nested data structure. HLM takes consideration of the nested data structure (teachers are nested within districts) and allows for partitioning the variation into within- and between groups with fewer assumptions for between and within-group differences [71]. HLM is more efficient at accounting for variance among variables at different levels than other existing analyses and thus allows us to consider impacts in the complex systems of education [65, 72]. Of specific interest was the relationship between the CT concepts and approaches (level-1 outcome variables) and both the teacher-level background and attitudes such as grade level, years of experience, stages of concern, confidence levels, and professional development frequencies (level-1 predictor variables) and their

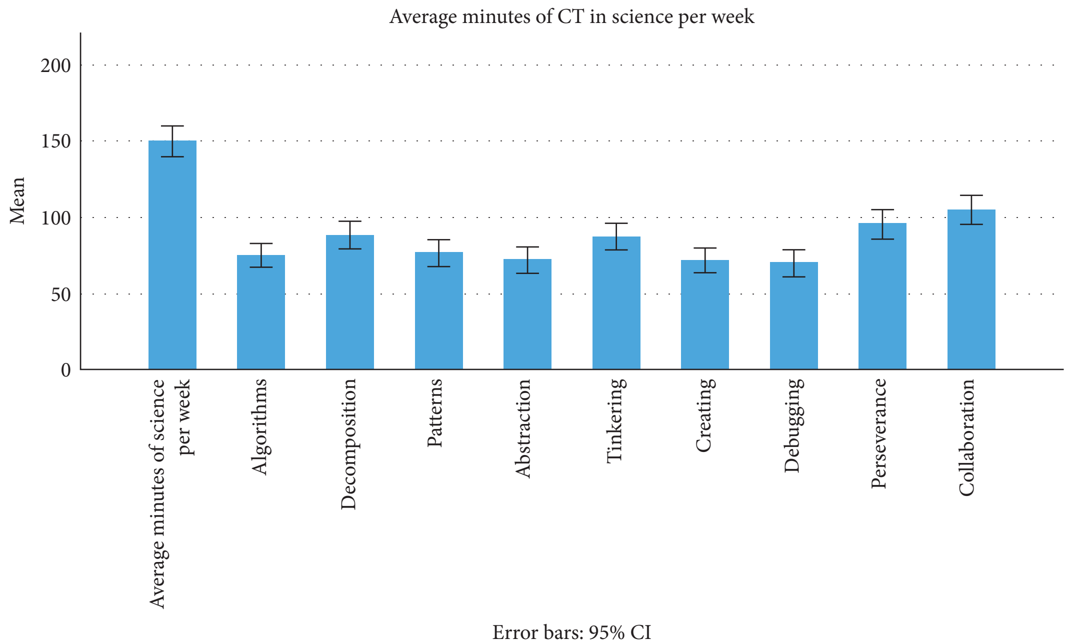

FIGURE 4: Average minutes of science instruction and CT components per week.

district classification, participation in an RPP, and district SES (level-2 predictor variables). The results can guide in-service science teacher professional development and curriculum development for integrating CT into what is already done in the classroom.

Level-1 equation examines the relationship between CT frequencies and teacher-level variables as follows:

$$\begin{aligned}\mathrm{CTMIN}_{ij} = {} & \beta_{0j} + \beta_{1j}(\mathrm{GRADE})_{ij} + \beta_{2j}(\mathrm{EXP})_{ij} + \beta_{3j}(\mathrm{PD})_{ij} \\ & + \beta_{4j}(\mathrm{CONFID})_{ij} + \beta_{5j}(\mathrm{CONCERN})_{ij} + \mathrm{r}_{ij}.\end{aligned} \tag{1}$$

Level-2 equation models the influence of district factors as follows:

$$\beta_j = \gamma_{00} + \gamma_{01}(\mathrm{LOCATION})_j + \gamma_{02}(\mathrm{SES})_j + \gamma_{03}(\mathrm{RPP})_j + \mathrm{u}_j. \tag{2}$$

5. Results

5.1. RQ1: Frequency of Teaching Computational Thinking (CT) Concepts and Approaches. CT concepts and approaches are currently being taught at different frequencies. Figure 4 shows the average minutes per week teachers spent teaching the different CT concepts and approaches. The amount of time was calculated using the total minutes of science taught per week multiplied by the percentage of time teachers indicated teaching the different CT concepts and approaches. Based on this data, the concept with the greatest average amount of minutes spent was decomposition with a mean of 89.75 min per week, followed by the teaching patterns (78.32 min), algorithms (75.17 min), and abstraction (73.18 min). The approach with the most time spent was collaboration with a mean of 108 min per week. This was followed by perseverance (95.20 min), tinkering (89.58 min), creating (73.56 min), and in last debugging (69.79). Time spent on collaboration was significantly more than debugging and creating.

Further analysis revealed 20% of teachers were teaching the different concepts and approaches for less than 30 min per week in comparison to the average teaching time of science at 151 min per week. This average teaching time is higher than the national average reported by the National Survey of Science and Math Education (NSSME) of 20 min per day but only half the National Science Teachers Association (NSTA) recommended amount of time of at least 60 min per day [73, 74]. More than half of the teachers spent less than an hour per week teaching algorithms, patterns, abstraction, debugging, and creating. More than 25% of the teachers spent over 2-hr teaching students how to decompose problems. More than 25% of teachers also taught lessons that included tinkering, persevering, and collaborating more than 2 hrs a week. When analyzing the times of the different CT concepts and approaches it is important to note that they are not taught independently of one another but can be taught intertwined with other content goals. This means creating and debugging can be happening at the same time as collaboration is happening in instruction.

5.2. RQ2: Impact of Teacher and District Characteristics on the Frequency of Teaching CT Concepts and Approaches. This question asks how district contexts and policies along with teacher characteristics affect the frequency of teaching CT concepts and approaches. When deciding on the most appropriate models, a series of steps and decisions were made. First, unconditional models were analyzed using an original data set consisting of science teacher responses from 30 different districts collected for each outcome variable, consisting of total minutes per week of the algorithms,

Table 2: HLM models for algorithms.

Fixed effect	Algorithms											
	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio
Intercept (γ_{00})	75.76	7.59	9.98**	75.68	7.49	10.10**	69.11	7.75	8.91**	65.09	8.04	8.10**
RPP curriculum (γ_{01})							24.16	14.10	1.713	32.96	14.05	2.34*
Poverty (γ_{02})							−1.07	0.65	−1.63			
Teaching experience (γ_{10})				5.87	3.98	1.47	5.87	3.98	1.48	5.87	3.97	1.48
Grade level (γ_{20})				10.97	3.23	3.40**	10.97	3.22	3.40**	10.97	3.22	3.41**
Confidence (γ_{30})				17.16	7.97	2.15*	17.16	7.96	2.16*	17.16	7.95	2.16*
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	3,895.40			3,423.94			3,414.22			3,404.40		
Level 2 (u_0)	390.05			417.19			161.93			248.67		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	90.90%			12.10%			12.35%			12.60%		
Level 2	9.10%						61.19%			40.39%		
Deviance (df)	1,635.21 (2)			1,598.09 (2)			1,582.61 (2)			1,587.87 (2)		

*$p<0.05$, **$p<0.01$.

Table 3: HLM models for decomposition.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio
Intercept (γ_{00})	90.12	8.61	10.46**	89.72	8.45	10.61**	81.79	10.15	8.05**	79.82	9.66	8.26**
RPP curriculum (γ_{01})							25.78	18.37	1.40	30.96	16.82	1.84
Poverty (γ_{02})							−0.66	0.87	−0.76			
Teaching experience (γ_{10})				7.83	4.25	1.84	7.83	4.25	1.84	7.83	4.25	1.84
Grade level (γ_{20})				12.55	3.45	3.64**	12.55	3.45	3.64**	12.55	3.44	3.64**
Confidence (γ_{30})				28.78	8.52	3.38**	28.78	8.50	3.38**	28.78	8.50	3.39**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	4,784.91			3,909.95			3,897.74			3,893.70		
Level 2 (u_0)	524.99			578.11			478.82			457.15		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	90.11%			18.29%			18.54%			18.63%		
Level 2	9.89%						17.17%			20.92%		
Deviance (df)	1,665.83 (2)			1,618.46 (2)			1,605.62 (2)			1,609.58 (2)		

**$p<0.01$.

decomposition, patterns, abstraction, tinkering, creating, debugging, perseverance, and collaboration. An unconditional model denotes the model with no predictors at either level. This model provides valuable information on the reliability of the slope estimates and the proportion of variance within and between districts. Out of 30 districts in the original data, only 15 districts had 5 or more participants. The effects of Level 2 predictors are not measured reliably if the number of participants per unit in level-2 is small. It was decided to run the subsequent analyses using the 15 districts with five or more teachers per district ($N=222$). First, unconditional models with no predictors at both teacher and district levels were examined as a baseline to which other models are compared. This model provides valuable information on the reliability of the slope estimates and the proportion of variance within and between districts.

Once the baseline unconditional models (Model 1 in Tables 2–10) were determined, the full saturated models were examined, allowing the slopes of all level-1 predictors (years of teaching experience, levels of concern, confidence, grade level, and professional development frequency) to be random. After examining the random slope models, it was decided to fix all the slope parameters as many slopes did not vary across districts (no significant random variations).

Among the five level-1 predictors, only three were statistically significant predictors of the outcomes: teacher experience, grade level, and teacher confidence levels. Levels of concern and professional development frequency were not significant factors for all nine dependent variables. To build the most parsimonious level-1 model, it was decided to include only three predictors (Model 2 in Tables 2–10). Next, full level-2 models included two district-context

Table 4: HLM models for patterns.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	81.20	8.01	10.14**	81.05	7.88	10.28**	74.56	9.22	8.09**	71.36	9.00	7.93**
RPP curriculum (γ_{01})							22.10	16.69	1.32	29.88	15.70	1.90
Poverty (γ_{02})							−0.96	0.78	−1.22			
Teaching experience (γ_{10})				10.37	4.19	2.48*	10.37	4.18	2.49*	10.37	4.17	2.49*
Grade level (γ_{20})				8.88	3.40	2.61**	8.88	3.38	2.62*	8.88	3.39	2.62**
Confidence (γ_{30})				29.43	8.38	3.51**	29.43	8.35	3.52**	29.43	8.35	3.52**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	4,518.75			3,785.74			3,760.20			3,762.63		
Level 2 (u_0)	415.77			462.79			335.35			359.51		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	91.58%			16.22%			16.79%			16.73%		
Level 2	8.42%						27.54%			22.32%		
Deviance (df)	1,656.37 (2)			1,612.48 (2)			1,598.83 (2)			1,603.49 (2)		

*$p<0.05$, **$p<0.01$.

Table 5: HLM models for abstraction.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	75.16	7.80	9.64**	74.83	7.64	9.79	71.16	8.76	8.13**	66.65	8.95	7.45**
RPP curriculum (γ_{01})							15.19	15.89	0.96	25.33	15.63	1.62
Poverty (γ_{02})							−1.20	0.74	−1.62			
Teaching experience (γ_{10})				9.87	4.28	2.31*	9.87	4.27	2.31*	9.87	4.27	2.31*
Grade level (γ_{20})				13.77	3.47	3.97**	13.77	3.46	3.98**	13.77	3.46	3.98**
Confidence (γ_{30})				29.19	8.57	3.41**	29.19	8.55	3.42**	29.19	8.55	3.41**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	4,996.69			3,956.27			3,938.95			3,939.53		
Level 2 (u_0)	325.58			394.57			247.04			334.47		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	93.88%			20.82%			21.17%			21.16%		
Level 2	6.12%						37.39%			15.23%		
Deviance (df)	1,669.16 (2)			1,617.44 (2)			1,603.79 (2)			1,609.37 (2)		

*$p<0.05$, **$p<0.01$.

Table 6: HLM models for tinkering.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	89.92	7.73	11.63**	89.67	7.69	11.67**	83.44	9.34	8.94**	80.74	8.87	9.10**
RPP curriculum (γ_{01})							1.26	16.93	1.26	27.89	15.51	1.80
Poverty (γ_{02})							−.82	0.79	−1.03			
Teaching experience (γ_{10})				5.36	4.42	1.21	5.36	4.40	1.22	5.36	4.40	1.22
Grade level (γ_{20})				12.64	3.58	3.53**	12.64	3.57	3.54**	12.64	3.57	3.54**
Confidence (γ_{30})				23.53	8.84	2.66**	23.53	8.80	2.67**	25.53	8.81	2.67**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	4,901.09			4,210.82			4,177.74			4,185.22		
Level 2 (u_0)	321.83			378.42			311.35			299.26		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	93.95%			19.38%			14.76%			14.61%		
Level 2	6.05%						17.72%			20.92%		
Deviance (df)	1,666.38 (2)			1,625.72 (2)			1612.82 (2)			1,617.09 (2)		

**$p<0.01$.

Table 7: HLM models for creating.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	75.88	7.23	10.49**	75.73	7.16	10.58**	74.18	8.11	9.14**	69.48	8.50	8.17**
RPP curriculum (γ_{01})							8.94	14.73	0.61	19.29	14.83	1.30
Poverty (γ_{02})							−1.27	0.69	−1.85			
Teaching experience (γ_{10})				7.52	4.00	1.88	7.52	3.99	1.88	7.52	4.00	1.88
Grade level (γ_{20})				7.80	3.24	2.40**	7.80	3.24	2.41*	7.80	3.24	2.40*
Confidence (γ_{30})				22.83	8.00	2.85**	22.83	7.99	2.86	22.83	8.00	2.85**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	3,892.84			3,449.70			3,445.58			3,450.14		
Level 2 (u_0)	319.19			348.03			205.89			311.05		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	92.42%			11.38%			11.49%			11.37%		
Level 2	7.58%						40.84%			10.63%		
Deviance (df)	1,633.93 (2)			1,597.92 (2)			1,584.74 (2)			1,590.85 (2)		

*$p < 0.05$, **$p < 0.01$.

Table 8: HLM models for debugging.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	74.45	7.55	9.86**	74.26	7.40	10.03**	68.42	7.75	8.83**	63.83	7.94	8.04**
RPP curriculum (γ_{01})							23.49	14.17	1.66	33.10	13.97	2.37*
Poverty (γ_{02})							−1.07	0.65	−1.66			
Teaching experience (γ_{10})				9.41	4.39	2.14*	9.41	4.37	2.15*	9.41	4.37	2.15*
Grade level (γ_{20})				13.90	3.56	3.90**	13.90	3.55	3.92**	13.90	3.55	3.92**
Confidence (γ_{30})				27.70	8.79	3.15**	27.70	8.75	3.17*	27.70	8.75	3.17**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	5,148.82			4,162.14			4,128.70			4,126.19		
Level 2 (u_0)	263.49			325.08			95.17			172.61		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	95.13%			19.16%			19.81%			19.86%		
Level 2	4.87%						70.72%			46.90%		
Deviance (df)	1,672.42 (2)			1,623.29 (2)			1,607.51 (2)			1,612.88 (2)		

*$p < 0.05$, **$p < 0.01$.

Table 9: HLM models for perseverance.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio	Coeff.	S.E.	*t*-Ratio
Intercept (γ_{00})	100.42	8.93	11.24**	100.26	8.87	11.30**	91.72	9.04	10.15**	86.41	9.29	9.30**
RPP curriculum (γ_{01})							31.00	16.44	1.89	42.99	16.26	2.64*
Poverty (γ_{02})							−1.36	0.76	−1.78			
Teaching experience (γ_{10})				7.25	4.66	1.56	7.25	4.62	1.57	7.25	4.63	1.57
Grade level (γ_{20})				15.44	3.78	4.09**	15.44	3.75	4.12**	15.44	3.75	4.11**
Confidence (γ_{30})				33.79	9.32	3.63**	33.79	9.25	3.65**	33.79	9.26	3.65**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	5,920.08			4,680.57			4,611.21			4,624.78		
Level 2 (u_0)	488.93			596.24			222.84			326.08		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	92.37%			20.94%			22.11%			21.88%		
Level 2	7.63%						62.63%			45.31%		
Deviance (df)	1,695.18 (2)			1,643.10 (2)			1,625.04 (2)			1,631.21 (2)		

*$p < 0.05$, **$p < 0.01$.

Table 10: HLM models for collaboration.

Fixed effect	Model 1			Model 2			Model 3			Model 4		
	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio	Coeff.	S.E.	t-Ratio
Intercept (γ_{00})	108.36	8.60	12.60**	108.07	8.42	12.83**	101.5	9.36	10.84**	97.07	9.37	10.36**
RPP curriculum (γ_{01})							24.55	17.00	1.44	34.56	16.39	2.11
Poverty (γ_{02})							−1.19	0.79	−1.51			
Teaching experience (γ_{10})				9.27	4.63	2.00*	9.27	4.61	2.01*	9.27	4.61	2.01*
Grade level (γ_{20})				15.31	3.75	4.08**	15.31	3.74	4.09**	15.31	3.74	4.09**
Confidence (γ_{30})				27.37	9.27	2.95**	27.37	9.23	2.97*	27.37	9.23	2.96**
Random effect	Variance			Variance			Variance			Variance		
Level 1 (r)	5,711.10			4,628.21			4,590.10			4,596.16		
Level 2 (u_0)	430.62			496.98			273.66			341.24		
Variance	Partitioned			Explained			Explained			Explained		
Level 1	92.99%			18.96%			19.63%			19.52%		
Level 2	7.01%						44.94%			31.34%		
Deviance (df)	1,689.42 (2)			1,640.34 (2)			1,625.16 (2)			1,630.57 (2)		

*$p<0.05$, **$p<0.01$.

variables and one policy variable: location, SES, and participation in an RPP. In searching for the most appropriate and parsimonious level-2 models, a decision was made to exclude district-classification variables, include an RPP curriculum, and present the results with and without percentages of families below the poverty level (Model 3 and Model 4 in Tables 2–10).

Model 1: unconditional model ($\text{CTMIN}_{ij} = \gamma_{00} + u_{0j} + r_{ij}$)

Model 1 (unconditional models) shows that over 90% of the variance in CT concepts and approaches lay within districts and less than 10% lay among districts, indicating most of the variances lie at the teacher level, ranging from 95% (debugging) to 90% (decomposition). Model 1 also serves as a baseline model against which the following models are compared in terms of variance explained in the model.

Model 2: fixed level-1 model ($\text{CTMIN}_{ij} = \beta_{0j} + \beta_{1j} {}^*(\text{EDUTIME}_{ij}) + \beta_{2j} {}^*(\text{GRADELEV}_{ij}) + \beta_{3j} {}^*(\text{CONFID}_{ij}) + r_{ij}$)

Model 2 includes the three teacher-level predictors: teaching experience, grade level, and confidence. The teaching experience was a significant predictor for the concepts of abstraction and recognizing patterns but not for algorithms or decomposition. The teaching experience was significant for the CT approaches of debugging and collaboration but not for tinkering, creating, or persevering. Both grade-level and confidence levels were significant for all the concepts and approaches. As grade levels increased from kindergarten to fifth grade, the time spent teaching computational concepts and approaches increased, which aligns with children being able to participate in more problem-solving skills as they increase in age [75]. As confidence levels increased, so did time teaching concepts and approaches. Teachers who believe they can do something well are more likely to spend more time doing it than someone uncertain of their ability [57].

The explained variance in Model 2 was different for each of the CT concepts and approaches. Abstraction had the highest variance among the CT concepts explained by the teacher-level factors at 20.82%, whereas algorithms were explained by only 12.10%. Perseverance was the CT approach with the highest variance explained at 20.94%, whereas creating had the lowest of the CT approaches at 11.38%. It is noted that 20.82% of variance explained in Model 2 is out of 93.88% of variance that lies between teachers for abstraction.

Model 3: full model with an RPP and district SES ($\text{CTMIN}_{ij} = \gamma_{00} + \gamma_{01} {}^*\text{RPPNET}_j + \gamma_{02} {}^*\text{POVERTY}_j + \gamma_{10} {}^*\text{EDUTIME}_{ij} + \gamma_{20} {}^*\text{GRADELEV}_{ij} + \gamma_{30} {}^*\text{CONFID}_{ij} + u_{0j} + r_{ij}$)

Model 3 includes two level-2 predictor variables: participating in an RPP and SES using the percentage of families with income below the poverty level as a proxy. None of the district-level predictors were significant when they were entered together. The proportion of variances explained by the two district variables ranged from 17.17% (decomposition) to 61.19% (algorithms) for the CT concepts. It ranged from 17.72% (tinkering) to 70.72% (debugging) for the CT approaches.

Model 4: full model with an RPP only ($\text{CTMIN}_{ij} = \gamma_{00} + \gamma_{01} {}^*RPP_j + \gamma_{10} {}^*\text{EDUTIME}_{ij} + \gamma_{20} {}^*\text{GRADELEV}_{ij} + \gamma_{30} {}^*\text{CONFID}_{ij} + u_{0j} + r_{ij}$)

Model 4 included only one level-2 predictor (participation in an RPP) because it was suspected there was a lot of shared variance when using the two predictor variables. This variable was of particular interest because it is a policy traceable variable whereas others were context variables. Participation in an RPP was found to have significant effects on the algorithms, debugging, and perseverance, after controlling for the effects of teacher-level predictors. It was not a significant predictor for decomposition, abstraction, recognizing patterns, tinkering, creating, and collaborating. The percentage of between-district variances explained by the RPP variable was 40.39% for algorithms, 46.90% for debugging, and 45.31% for perseverance.

Results showed that the teacher-level variables played a significant role in determining the time spent teaching CT skills. The bottom portion of Tables 2–10 shows the percentage of variance explained by the different models. The teacher's years of experience, grade level being taught, and confidence levels explained 11%–21% of the level-1 variances (between teachers). The engagement in an RPP explains 40%–47% (Model 4) of these CT concepts and approaches.

6. Discussion

Elementary classrooms are nested in the complex social and political layers that impact curricular decisions and teachers of young students are impacted by competing priorities among content experts. As teachers and districts gather research, abide by educational policy, and react to current events, their daily decisions about how much time is spent teaching which subject varies. With consideration for the social layers and competing content priorities that elementary classrooms already face, the growing need to implement CT calls for creative and thoughtful implementation. This study was performed to explore the landscape of what already exists in classrooms throughout a northeast state and analyze variables at the teacher level (microsystem layer) and the district level (exosystem layer) that are conducive to incorporating CT within the school day.

In answering the first research question concerning how often CT concepts and approaches are currently taught in K–5 science classrooms, teachers reported that CT concepts and approaches overlapped with approximately half of their science instruction. While it is promising that CT exists so readily in current science instruction, the research also found that the elementary teachers only spent 7% of their instructional time each week teaching science. Decomposition, collaboration, persevering, and tinkering were more likely to be included in the lessons than algorithms, patterns, abstraction, and debugging. Example responses from teachers who took this survey include decomposition, "determining/labeling the parts of a cell", collaboration, "working as a team to solve a problem", persevering, "when creating a structure to hold a book, multiple trials are needed", and tinkering, "figuring out how to make a light bulb light up with wires and a battery. After determining where the concepts and approaches exist in the curriculum, teacher efforts should enhance the CT examples by explicitly identifying and stating the CT terminology (decomposition, collaboration, persevering, etc.) in their lessons. Teachers may need additional support when integrating creating, debugging, recognizing patterns, and using abstraction into science instruction because these are the areas where more complex thinking and skills are involved. They may need possible opportunities identified for them as to where these concepts and approaches could exist in their curriculum. Prioritizing more time on science at the elementary level has potential for more CT opportunities which instill early computer science knowledge and skills with minimal curricula shifts.

Teacher factors from the microsystem layer and district factors from the exosystem layer were analyzed using an HLM to determine if they had an impact on the teaching of CT skills. In answering the second research question, concerning the analysis of teacher characteristics in relation to the frequency of CT concepts and approaches, the results show that experience in teaching, grade level, and confidence were significant predictors, whereas professional development experience and levels of concern were not significant predictors. Teachers with more experience are more likely to engage in science activities that include CT concepts and approaches of debugging, collaboration, patterns, and abstraction. The concepts of recognizing patterns and abstraction involve utilizing higher order thinking skills when taught. Perhaps experienced teachers are more intentional in promoting higher order thinking, which successfully advances critical thinking [46]. Experienced teachers could serve as mentors to novice teachers for helping them integrate CT concepts.

As the grade level increases, the frequency of teaching CT concepts and approaches increases. This finding was not surprising at all because developmentally, students can engage in more complex thinking as they progress through the grades that teachers consider when teaching their lessons. Rijke et al. [75] found that students between the ages of 6 and 12 increased their usage of performing abstraction on a task as they increased in age. Kale et al.'s [54] study looking at teachers' CT skills and usage found primary school teachers used significantly fewer CT skills than teachers from the secondary level. The NGSS in the United States [9] also have CT standards which increase in frequency with rising grade levels. Examples from the ISTE standards for educators for finding CT opportunities in existing lessons also show an increase in the number of concepts consisting of the abstraction, algorithms, pattern recognition, and decomposition for rising grade levels [16].

Teachers' level of confidence in teaching CT was also a significant variable for determining CT frequency. This is a noteworthy finding because districts can provide resources to help increase their staff's confidence levels by implementing professional development that utilizes engaging tools and support structures [43, 47, 51, 55, 76]. Strategies used during professional development that should be considered are active learning, reflection, collaboration, receiving feedback from coaches and instructors, and mentoring [58, 77]. Four factors responsible for increasing confidence or self-efficacy are mastery, vicarious experience, social and verbal persuasion, and increasing physical and emotional states [57]. Effective professional development for mastery includes teaching both content and pedagogy. Creating vicarious experiences can happen through collaboration and mentoring. Social and verbal persuasion can improve confidence through a supportive culture and providing positive feedback. Increasing physical states can be achieved through student-centered instruction and increasing positive emotional states through getting teachers to have a shared vision of making a difference in student learning [57, 58, 78, 79]. Teachers are more likely to engage in a practice if they feel like they can be successful at achieving results [57] so building communities of practice that evaluate instruction and student work and provide informative feedback will also build confidence. In addition, professional development opportunities have been shown to improve teachers' confidence and self-efficacy when integrating CT [55, 80, 81].

While high-quality professional development is commonly linked to implementation and understanding interdisciplinary science concepts [82, 83], 70% of teachers had “no to little” professional development in computer science implementation, only 30% had more than 3 hrs. The overall lack of professional development experience, the professional development’s relevance to elementary instruction, and those with professional development might have more critically judged their science activities for CT, might explain these outcomes. Therefore, professional development should not be a factor that is ruled out when working toward building teachers’ confidence. Students will not understand CT until teachers understand and feel confident about their abilities [44]. This study did not disprove the effects of professional development on the integration of CT in science. Future studies are required to identify the influence of professional development on the use of CT in the science instruction, especially the PDs using strategies that increase teachers’ confidence.

A similar pattern was seen in the teachers’ level of concern for implementing CT in that they had low stages of concern. Research has indicated that as teachers increase their concern for an innovation, they engage in the innovation more often [53, 84]. Teachers’ level of concern for implementing CT was at the early stages in this study. In fact, most teachers (61%) reported that they only “may have heard something about it” or “might want to know more about it, but that other responsibilities take priority.” Awareness of the importance of CT needs to be built through professional learning opportunities and district initiatives. Stages of concern most likely will change once teachers learn the value of CT and start engaging with it in their teaching and learning.

The analysis of district-level variables in relation to the frequency of CT concepts and approaches, show that location was not a significant predictor whereas district SES and participation in an RPP may be significant predictors for the use of CT in the science instruction. When each variable was examined alone, both SES and the RPP variable were significant predictors. However, they lost significance when the two variables were entered together. When using only SES as the predictor variable, there were differences in the teaching and learning of algorithms, abstraction, creating, debugging, perseverance, and collaboration. As the percentage of families with low-SES increased, the use of CT concepts and approaches decreased. There were also differences when using only the RPP curriculumas the predictor variable for algorithms, debugging, and perseverance. The interaction between SES levels and participation in an RPP was less significant due to the shared variance created by an RPP curriculum districts being more affluent when using only the 15 districts through the HLM analysis. When analyzing the percentage of families with income below the poverty level (11%–40% below poverty) from these 15 districts, 57% of the RPP districts made up this population, whereas districts without RPPs made up 75%. Although there is some indication that the RPP influences the use of CT integration in science, further studies involving more participation by less affluent districts in the RPP are warranted to accurately determine if an RPP predicts more CT usage for all concepts and approaches.

The RPP that teachers belong to in this study is mandated at the district level and has been supporting science education for 21 years. Teachers receive on-going mandatory professional development on standards-based science instruction. Prior to this study the RPP had not intentionally aimed to integrate CT into the science instruction, beyond what is called for in the science and engineering standards. However, all teachers had professional development that encouraged students to engage in the deep-thinking work of scientists. RPPs help teachers to become more aware of effective practices based on the current research and allow them to be more comfortable in taking risks by having others to share in their successes and failures [63]. This research study has demonstrated that districts using an RPP curriculum may be more apt to integrate CT into their everyday lessons. Being part of an RPP with continuous mandatory PD affords teachers the resources to facilitate the learning of more complex concepts by having time and space to discuss what is going well in their instruction.

6.1. Implications and Recommendations. This research brings awareness to the complex systems associated with elementary school instruction that impact the implementation of new innovations. Based on the data from teachers’ surveys, there is exciting potential to integrate CT into daily science instruction. While the concepts and approaches of decomposition, collaboration, persevering, and tinkering might integrate more effortlessly, creating, debugging, patterns and abstraction may need extra support through professional development and targeted curricula. In addition, CT is integrated into science lessons more often as grade levels progress. Extra support for understanding and implementing CT at the earliest grades would have the greatest impact, particularly as the concern for the digitally literate problem-solvers increase to meet the needs of our complex world. The increase of teachers’ years of experience with teaching and their confidence in teaching CT predicted a greater amount of CT integration. Therefore, preservice teacher preparatory programs should incorporate CT integration in their content methods courses and ongoing professional development should be provided to increase self-efficacies for the all teachers. In addition, pairing experienced, confident teachers with less experienced and less confident teachers may increase CT integration. While teacher-level factors had a greater influence on the integration of CT than the district level, participation in an RPP may positively influence CT integration and SES may have a negative influence. Providing more resources at all layers of the educational system, but particularly for schools in low-income areas is needed to ensure children develop CT skills effectively and equitably so they can be active participants in a digitally rich and problem-driven society.

Schools should be encouraged to join an RPP with their local universities. Without follow-up support for teachers, the outcomes from professional development decline over time [85]. Being part of a sustained RPP would prevent this decline and provide the support needed as new best practices emerge from research and new concepts and skills are needed as technology advances. Additional research is needed on how the systems approach and sustainable teacher development of an RPP may leverage science curricula and increase science teachers' ability to integrate CT into their instruction.

Appendix

Computational Thinking in Elementary School Classrooms

Welcome to the Computational Thinking Survey. This survey is being conducted to understand the concepts and approaches to computational thinking being used in K–5 Schools. Your participation is voluntary. No personally identifiable information will be associated with your responses in any reports of the data. Upon completion of this survey, a form from URI will be available to print out for 1 PLU (professional learning unit) credit. If you have any questions or comments about the survey, please feel free to contact Sara Sweetman, the study director, by email at sara_sweetman@uri.edu or by phone (401) 874-600.

(1) Do you agree to participate in this survey?
- ○ Yes, I agree to participate.
- ○ No, I do not agree to participate.

(2) Which statement best describes your concern about teaching computational thinking curriculum in elementary school?
- ○ "I'm concerned about the changes I will need to make in my routine."
- ○ "I'm concerned about how much time it will take to get ready to teach with this new approach."
- ○ "How will this new approach impact my students?"
- ○ "I incorporate computational thinking skills into my lessons now and have ideasabout how to do it better."

(3) How would you rate your confidence level incomputational thinking?
- ○ Extremely confident
- ○ Very confident
- ○ Somewhat confident
- ○ Not so confident
- ○ Not at all confident

(4) How would you define your gender?
- ○ Female
- ○ Male
- ○ Nonbinary
- ○ Prefer to self-describe.

(5) Which race/ethnicity best describes you? (Please choose only one)
- ○ American Indian or Alaskan Native
- ○ Asian/Pacific Islander
- ○ Blackor African American
- ○ Hispanic
- ○ White/Caucasian
- ○ Multiple ethnicity/other (Please specify)

____

(6) In which school district or educational organization are you employed or are representing?

____

(7) What is the name of your school?

____

(8) How long have you been an educator?
- ○ 0–3 years
- ○ 4–6 years
- ○ 7–10 years
- ○ 11–15 years
- ○ 16–20 years
- ○ 20+ years

(9) How long have you been in your current position?
- ○ 0–3 years
- ○ 4–6 years
- ○ 7–10 years
- ○ 11–15 years
- ○ 16–20 years
- ○ 20+ years

(10) What areas are you certified in?

____

(11) What is the highest level of education you have completed?
- ○ Bachelor's Degree
- ○ Some graduate school
- ○ Master's Degree
- ○ Master's Degree plus additional credits
- ○ PhD/EdD

(12) What grade(s) do you teach? Select all that apply.
- ☐ Kindergarten
- ☐ First Grade
- ☐ Second Grade
- ☐ Third Grade
- ☐ Fourth Grade
- ☐ Fifth Grade
- ☐ Other (please specify)

____

(13) What subjects do you teach? Select all that apply.
- ☐ Math

☐ Science
☐ Social Studies
☐ English or Language Arts
☐ After school computer programming
☐ Other specialization (please specify)

____

(14) On average how many days a week are your students taught each of the following subjects?

	0	1	2	3	4	5
ELA	○	○	○	○	○	○
Math	○	○	○	○	○	○
Science	○	○	○	○	○	○
Social studies	○	○	○	○	○	○
Specialization	○	○	○	○	○	○

(15) On average how many minutes is a typical lesson in each of the following subjects?

	0–20 min	21–40 min	41–60 min	61–80 min	81–100 min	>than 100 min
ELA	○	○	○	○	○	○
Math	○	○	○	○	○	○
Science	○	○	○	○	○	○
Social studies	○	○	○	○	○	○
Specialization	○	○	○	○	○	○

(16) What type of science curriculum are you using? (Check all that apply)
☐ Stem scopes
☐ Gizmos
☐ Gems-Net/Foss
☐ Kit-based curriculum
☐ Open SciEd
☐ Make my own lessons.
☐ Other (please specify)

____

(17) How often do you use technology for instruction in your classroom?
☐ Most lessons each day
☐ Afew lessons each day
☐ One lesson a day
☐ A few lessons each week
☐ A few lessons each month
☐ A few lessons each year
☐ Never

(18) Briefly describe or list the types of technology you or your students are using.

____

(19) CT is a problem-solving process that includes a number ofcharacteristics and dispositions. CT is essential to the development ofcomputer applications, but it can also be used to support problem-solving across all disciplines, including the humanities, math, and science. Students who learn CT across the curriculum can begin to see a relationship between academic subjects, as well as between life inside and outside of the classroom ("Google Computational Thinking for Educators," n.d.).

CT allows us to take a complex problem, understand what the problem is and develop possible solutions in a way that a computer, a human, or both, can understand (https://www.bbc.com/bitesize/guides/zp92mp3/revision/1).

Based on these definitions, how often do you think you apply computational thinking in your classroom?
○ Most lessons each day
○ A few lessons each day
○ One lesson a day
○ A few lessons each week
○ A few lessons each month
○ A few lessons each year
○ Never

For each of the CT concepts and approaches, we describe the concept or approach and then ask you to share how often you teach or use the concept or approach in each subject. Finally, we ask for an example of how you might teach this in the classroom. You do not have to give an example for each concept and approach. It is our hope that out of the different concepts and approaches you pick just a few to share a short (a few sentences) example description with us.

Concept: Algorithms. An algorithm is "a sequence of instructions or a set of rules to get something done. Computer scientists strive for algorithms which solve problems in the most-effective and efficient ways-getting the most accurate results, in the quickest time, with the fewest resources (memory or time)" (Barefoot Computing, n.d.).

When students come up with their own sequences of instructions, for example, how to get dressed or clean their teeth, create a plan for a story, write instructions for a game or sport, develop rules for grammar or math, the are creating algorithms as shown in Figure 5 (https://www.barefootcas.org.uk).

(20) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching about or having the students engage in algorithms?

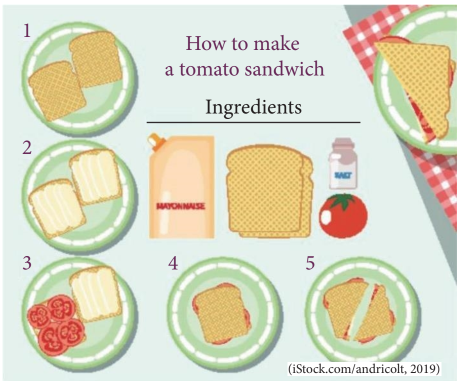

Figure 5: This is an example of an algorithm for making a tomato sandwich.

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(21) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching algorithms?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(22) In a sentence or two describe a lesson you taught that includes *algorithms* in the teaching and learning process (optional).

____

Concept: Decomposition. Decomposition is "the process of breaking down a task into smaller, more-manageable parts. It has many advantages. It helps us to manage large projects and makes the process of solving a complex problem less daunting and much easier to take on" (Barefoot Computing, n.d.). Whenever students are labeling, adding detail to concept maps, or creating instructions, life cycles, and timelines, they are practicing their decomposition skills (Figure 6). Solving a math problem, getting dressed for PE, planning a research project, or organizing a school event are other examples (https://www.barefootcas.org.uk).

(23) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching about or having the students engage in decomposition?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

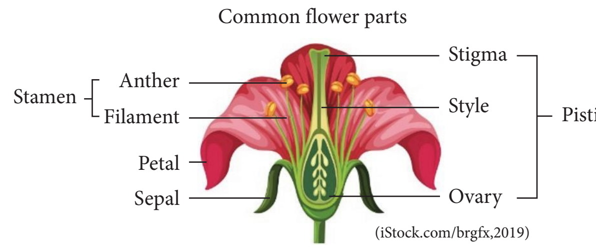

Figure 6: A flower is broken down into smaller parts.

Figure 7: Students look for patterns to construct a Sierpinski triangle.

(24) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching decomposition?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(25) In a sentence or two describe a lesson you taught that includes decomposition in the teaching and learning process (optional).

____

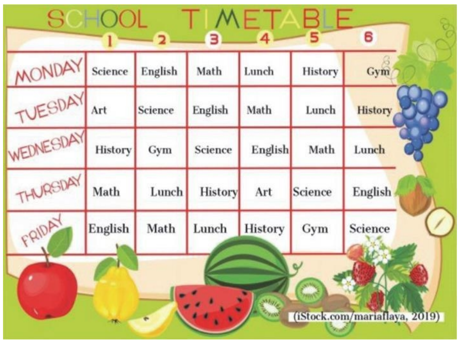

FIGURE 8: A timetable is an abstraction of the school day; much is omitted to summarize this occurrence.

Concept: Patterns. Patterns are described as "spotting similarities and common differences. By identifying patterns, we can make predictions, create rules, and solve more general problems" (Barefoot Computing, n.d.).

When children learn to recognize repeating melodies in music or phrases in stories, when they see similarities and differences in data collected in science, or rules or number sequences in math, they are identifying patterns (Figure 7) (https://www.barefootcas.org.uk).

(26) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching about or having the students engage in patterns?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(27) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching patterns?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(28) In a sentence or two describe a lesson you taught that includes *patterns* in the teaching and learning process (optional).

____

Concept: Abstraction. "Abstraction is about simplifying things-identifying what's important without worrying too much about detail" (Barefoot Computing, n.d.). For example, math word problems involve students identifying the key information and learning how to present the problem in the language of numbers. In geography, students use maps to represent an area without showing the complexity of the environment. Other examples of abstraction include creating a story plan or mind map where details are left out, making notes and charts of the most important properties in science, creating a presentation with key points on a topic, or making an argument with supporting information (Figure 8) (https://www.barefootcas.org.uk).

(29) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching or having the students engage in abstraction?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(30) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching abstraction?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(31) In a sentence or two describe a lesson you taught that includes abstraction in the teaching and learning process (optional).

____

Approach: Tinkering. Tinkering is an approach to thinking about where you try things out. This is the play-based, exploration and an experimentation phase of learning. Examples include children trying things out through role playing, exploring, asking why and how questions, figuring out how things work, building and creating, and testing new ideas (Figure 9) (https://www.barefootcas.org.uk).

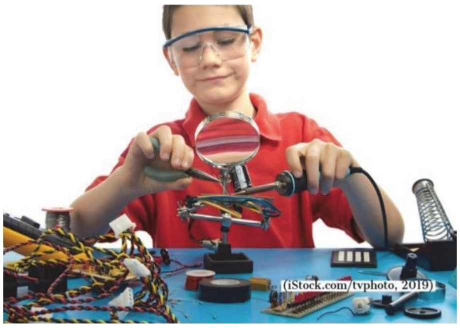

FIGURE 9: A boy is tinkering with different materials.

(32) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching about or having the students engage in tinkering?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(33) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching tinkering?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(34) In a sentence or two describe a lesson you taught that includes *tinkering* in the teaching and learning process (optional).

____

Approach: Creating. "Creating is about planning and making things. Some endeavors involve various media, each providing an outlet forcreative expression. Software and digital media allow scope for creativity and, by mastering software tools and digital devices, we develop confidence, competence, and independence which we can use playfully, experimentally, and purposefully in the expression of our ideas and insights (Figure 10) (Barefoot Computing, n.d.). Examples include students making games, animations, quizzes, models, artwork, toys, and inventions (https://www.barefootcas.org.uk).

(35) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching or having the students engage in creating?

FIGURE 10: The girl is creating a camouflage shirt to blend into the background.

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(36) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching creating?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(37) In a sentence or two describe a lesson you taught that includes creating in the teaching and learning process (optional).

____

Approach: Debugging. Debugging is an approach to thinking where students are finding and fixing errors through a process such as predicting what should happen, finding out exactly what did happen, working out where something went wrong, and fixing it (Figure 11). Examples include students find and fix errors in their work and their peers' work and find opportunities for improvement (https://www.barefootcas.org.uk).

(38) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching about or having the students engage in debugging?

Figure 11: The girl just debugged her program with the robot by fixing the algorithm.

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(39) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching debugging?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(40) In a sentence or two describe a lesson you taught that includes *debugging* in the teaching and learning process (optional).

____

Approach: Perseverance. Persevering is an approach to thinking where you never give up, you are determined, resilient, and tenacious. Examples occur in music, sports, and dance where students need to practice, train, and rehearse to improve their skills. Solving puzzles, building complex models, participating in activities that take many days, tackling difficult problems while experiencing confusion are other examples where students persevere (Figure 12) (https://www.barefootcas.org.uk).

(41) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching or having the students engage in perseverance?

Figure 12: The children are persevering with learning to play music together.

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(42) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching perseverance?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

(43) In a sentence or two describe a lesson you taught that includes *perseverance* in the teaching and learning process (optional).

____

Approach: Collaborating. Collaborating is an approach to thinking where you work with others to ensure the best result. Examples include students taking turns, working together, listening to each other, providing feedback, helping each other, and working as teams (Figure 13) (https://www.barefootcas.org.uk).

(44) Think about the last lesson you taught in each of the following subjects. What percentage of that lesson did you spend teaching or having the students engage in collaboration?

Subject	Percent of lessons
ELA	__________
Math	__________
Science/engineering	__________
Social studies	__________
Specialization	__________

FIGURE 13: The students collaborate with their project.

(45) Think about each subject curriculum as a whole (yearlong). On average, what percentage of time in that subject do you spend teaching collaboration?

Subject	Percent of lessons
ELA	________
Math	________
Science/engineering	________
Social studies	________
Specialization	________

(46) In a sentence or two describe a lesson you taught that includes *collaboration* in the teaching and learning process (optional).

____

(47) How often have you participated in professional development in computer science, computing, or computational thinking?
○ I have not had any professional development.
○ 1–3 hrs
○ 4–6 hrs
○ 7–10 hrs
○ 11–20 hrs
○ More than 20 hrs

(48) Could you describe the professional development you have received?

____

(49) What is your interest level in attending professional development for computational thinking?
○ Extremely interested
○ Very interested
○ Somewhat interested
○ Not so interested
○ Not at all interested

(50) Do you think computational thinking should be a priority in education?
○ Strongly agree
○ Agree
○ Neither agree nor disagree
○ Disagree
○ Strongly disagree

(51) Does your school district encourage computational thinking?
☐ Yes
☐ No

Please comment on your choice

____

(52) What supports would you like to see in the future to help you integrate computational thinking into your curriculum (optional)?

____

(53) Computational thinking is relevant to my current job functions.
○ Strongly agree
○ Agree
○ Neither agree nor disagree
○ Disagree
○ Strongly disagree

Now that you know more about computational thinking…

(54) Which statement best describes your concern about teaching computational thinking curriculum in elementary school?
○ “I’ve heard something about it, but other responsibilities take priority.”
○ “This seems interesting, and I would like to know more about it.”
○ “I’m concerned about the changes I will need to make in my routine.”
○ “I’m concerned about how much time it will take to get ready to teach with this new approach.”
○ “How will this new approach impact my students?”
○ “I’m looking forward to sharing some ideas about it with other teachers.”
○ “I incorporate computational thinking skills into my lessons now and have ideas about how to do it better.”

(55) How would you rate your confidence level in computational thinking?
○ Extremely confident
○ Very confident
○ Somewhat confident
○ Not so confident
○ Not at all confident

(56) Overall, how often do you think you apply computational thinking in your classroom?
○ Most lessons each day

○ A few lessons each day
○ One lesson a day
○ A few lessons each week
○ A few lessons each month
○ A few lessons each year
○ Never

Data Availability

The data that support the findings of this study are available from the corresponding author, (JP), upon reasonable request.

Additional Points

Limitations. There are several limitations that should be considered from this study. The first limitation is data were collected from a self-reported survey. Although a detailed description of each CT concept and approach using definitions, pictures, and examples were provided so teachers would have a common set of knowledge, the questions asked the teachers to remember lessons from the previous dates and weeks. Observations of actual lessons would provide more accurate data. Social desirability bias is likely because teachers would want to report they engage in high-level thinking practices and were likely to inflate the number of minutes they spent on each CT concept and skill. In addition, teachers who participated in taking the survey may have a higher level of interest and motivation around the subject matter than the typical elementary teacher population causing additional response bias.

The second limitation was the insufficient sample size for district-level analysis. The study was only able to include 15 out of 30 districts that participated in the survey due to insufficient numbers of teachers within each district responding to the survey. HLM was used to understand the nested nature of the data but the requirements for reliable estimates in the HLM analysis, caused a decrease in sample size from $N=259$ to $N=222$. Preliminary analysis shows that the excluded districts were mostly those serving lower SES communities. The effects of district RPP participation may be bigger for those districts serving the lower SES communities as it provides critical support for ongoing professional development activities. To investigate the effects of SES and RPP participation clearly and fully, data from these districts need to be collected in the future studies.

The third limitation is the DBIR team created the CT survey with the most up to date definitions at the time. Although these definitions were developed with the goal of teacher-friendliness, it is recognized that definitions are a work in progress and are constantly evolving. There still is no agreed upon definition in the literature. Moreover, the definitions may change as the needs and contexts change. Therefore, it is important that the computer science and education communities come together and decide on shared terminology of what CT is along with the skills involved at the elementary level. By having shared language, measuring progress on implementation efforts can be more accurately assessed.

There is a limitation in the availability of the data. The study did not include all layers of systems from the ecological systems theory. Moreover, learner outcomes are not included. Future studies examining the relationship between integration of CT in science and student learning outcomes would be interesting and beneficial.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References

[1] U. Wilensky, C. E. Brady, and M. S. Horn, "Fostering computational literacy in science classrooms," *Communications of the ACM*, vol. 57, no. 8, pp. 24–28, 2014.
[2] M. S. Khine, "Strategies for developing computational thinking," in *Computational Thinking in the STEM Disciplines*, pp. 3–9, Springer, Cham, 2018.
[3] S. Papert, *Mindstorms: Children, Computers, and Powerful Ideas*, Basic Books, Inc. Publishers, New York, 1980.
[4] Code.org, CSTA, & ECEP Alliance, "State of computer science education: accelerating action through advocacy," 2021, Retrieved from https://advocacy.code.org/stateofcs.
[5] J. M. Wing, "Computational thinking," *Communications of the ACM*, vol. 49, no. 3, pp. 33–35, 2006.
[6] V. Barr and C. Stephenson, "Bringing computational thinking to K–12: what is involved and what is the role of the computer science education community?" *ACM Inroads*, vol. 2, no. 1, pp. 48–54, 2011.
[7] S. Grover and R. Pea, "Computational thinking in K–12," *Educational Researcher*, vol. 42, no. 1, pp. 38–43, 2013.
[8] STE, CSTA, "Computational thinking in K–12 education leadership toolkit," 2011.
[9] NGSS Lead States, *Next Generation Science Standards: For States, by States*, National Academies Press, Washington, D.C, 2013.
[10] K. M. Rich, A. Yadav, and C. V. Schwarz, "Computational thinking, mathematics, and science: elementary teachers' perspectives on integration," *Journal of Technology & Teacher Education*, vol. 27, no. 4, pp. 165–205, 2019.
[11] V. J. Shute, C. Sun, and J. Asbell-Clarke, "Demystifying computational thinking," *Educational Research Review*, vol. 22, pp. 142–158, 2017.
[12] A. Yadav, S. Gretter, J. Good, and T. McLean, "Computational thinking in teacher education," in *Emerging Research, Practice, and Policy on Computational Thinking*, pp. 205–220, Springer, Cham, 2017.
[13] Computational Thinking for Educators, "Unit 1—introducing computational thinking," 2015, Retrieved from https://computationalthinkingcourse.withgoogle.com/unit.
[14] BBC, *What is Computational Thinking?—Introduction to Computational Thinking—KS3 Computer Science Revision–BBC BBC Bitesize*, BBC News, [Accessed: 3-Jul-2023] https://www.bbc.co.uk/bitesize/guides/zp92mp3/revision/1.
[15] M. Berry, *Computing in the National Curriculum: A Guide for Primary Teachers*, Computing at School, Bedford, 2013.

[16] K. Prottsman, *Computational Thinking Meets Student Learning: Extending the ISTE Standards*, International Society for Technology in Education, 2019.

[17] Barefoot Computing, 2019, Retrieved from https://www.barefootcomputing.org.

[18] K. Mills, M. Coenraad, P. Ruiz, Q. Burke, and J. Weisgrau, "Computational thinking for an inclusive world: a resource for educators to learn and lead," *Digital Promise*, 2021.

[19] Y. Baek, S. Wang, D. Yang, Y.-H. Ching, S. Swanson, and B. Chittoori, "Revisiting second graders' robotics with an understand/use-modify-create strategy," *European Journal of STEM Education*, vol. 4, no. 1, 2019.

[20] M. U. Bers, L. Flannery, E. R. Kazakoff, and A. Sullivan, "Computational thinking and tinkering: exploration of an early childhood robotics curriculum," *Computers & Education*, vol. 72, pp. 145–157, 2014.

[21] L. Üşengül and F. Bahçeci, "The effect of Lego Wedo 2.0 education on academic achievement and attitudes and computational thinking skills of learners toward science," *World Journal of Education*, vol. 10, no. 4, Article ID 83, 2020.

[22] S. Bocconi, A. Chioccariello, G. Dettori, A. Ferrari, and K. Engelhardt, *Developing Computational Thinking in Compulsory Education—Implications for Policy and Practice*, Publications Office, (No. JRC104188). Joint Research Centre (Seville site), 2016.

[23] D. Butler and M. Leahy, "Developing preservice teachers' understanding of computational thinking: a constructionist approach," *British Journal of Educational Technology*, vol. 52, no. 3, pp. 1060–1077, 2021.

[24] U. Bronfenbrenner, *The Ecology of Human Development: Experiments by Nature and Design*, Harvard University Press, Cambridge, MA, 1996.

[25] S. Grover, "The 5th 'C'of 21st century skills. Try computational thinking (not coding)," 2018, from EdSurge News https://www.edsurge.com/news/2018-02-25-the-5th-c-of-21st-century-skills-try-computational-thinking-not-coding.

[26] J. Kemi, U. Wilensky, L. Trouille et al., "Embedding computational thinking in science, technology, engineering, and math (CT-STEM)," in *Future Directions in Computer Science Education Summit Meeting*, Orlando, FL, 2014.

[27] D. Weintrop, E. Beheshti, M. Horn et al., "Defining computational thinking for mathematics and science classrooms," *Journal of Science Education and Technology*, vol. 25, no. 1, pp. 127–147, 2016.

[28] A. C. Bart, "Situating computational thinking with big data," in *Proceedings of the 46th ACM Technical Symposium on Computer Science Education*, SIGCSE, Article ID 719, 2015.

[29] Google Inc. & Gallup Inc, "Encouraging students toward computer science learning. Results from the 2015–2016 Google–Gallup study of computer science in U.S. K–12 schools (issue brief no. 5)," 2017, Retrieved from https://goo.gl/iM5g3A.

[30] D. Kafura, A. C. Bart, and B. Chowdhury, "A computational thinking course accessible to non-stem majors," *Journal of Computing Sciences in Colleges*, vol. 34, no. 2, pp. 157–163, 2018.

[31] J. R. McGinnis, D. J. Ketelhut, K. Mills, E. Hestness, H. Jeong, and L. Cabrera, "Preservice science teachers' intentions and avoidances to integrate computational thinking into their science lesson plans for young learners," in *Grantee Submission, Paper Presented at the Annual International Conference of NARST: A Worldwide Association for Research in Science Teaching and Learning*, ERIC, Baltimore, MD, 2019.

[32] F. Kalelioglu, Y. Gülbahar, and V. Kukul, "A framework for computational thinking based on a systematic research review," *Baltic Journal of Modern Computing*, vol. 4, no. 3, pp. 583–596, 2016.

[33] A. E. Weinberg, "*Computational Thinking: An Investigation of the Existing Scholarship and Research*," Doctoral dissertation, Colorado State University, 2013.

[34] I. Lee, S. Grover, F. Martin, S. Pillai, and J. Malyn-Smith, "Computational thinking from a disciplinary perspective: integrating computational thinking in K–12 science, technology, engineering, and mathematics education," *Journal of Science Education and Technology*, vol. 29, no. 1, pp. 1–8, 2020.

[35] Z. Karpinski, F. Biagi, and G. Di Pietro, *Computational Thinking, Socioeconomic Gaps, and Policy Implications. IEA Compass: Briefs in Education Number 12*, International Association for the Evaluation of Educational Achievement, Amsterdam, The Netherlands, 2021.

[36] A. V. Maltese and R. H. Tai, "Eyeballs in the fridge: sources of early interest in science," *International Journal of Science Education*, vol. 32, no. 5, pp. 669–685, 2010.

[37] M. U. Bers, *Coding as a Playground: Programming and Computational Thinking in the Early Childhood Classroom*, Routledge, Taylor & Francis Group, New York, 2021.

[38] S. Mattera and P. Morris, *Counting on Early Math Skills: Preliminary Kindergarten Impacts of the Making Pre-K Count and High 5s Programs*, MDRC, 2017.

[39] K. McIntosh, R. H. Horner, D. J. Chard, J. B. Boland, and R. H. Good, "The use of reading and behavior screening measures to predict nonresponse to school-wide positive behavior support: a longitudinal analysis," *School Psychology Review*, vol. 35, no. 2, pp. 275–291, 2006.

[40] Y.-C. Hsu, N. R. Irie, and Y.-H. Ching, "Computational thinking educational policy initiatives (CTEPI) across the globe," *TechTrends*, vol. 63, pp. 260–270, 2019.

[41] A. A. Ogegbo and U. Ramnarain, "A systematic review of computational thinking in science classrooms," *Studies in Science Education*, vol. 58, no. 2, pp. 203–230, 2022.

[42] P. Sands, A. Yadav, and J. Good, "Computational thinking in K–12: in-service teacher perceptions of computational thinking," in *Computational Thinking in the STEM Disciplines*, pp. 151–164, Springer, Cham, 2018.

[43] D. J. Ketelhut, K. Mills, E. Hestness, L. Cabrera, J. Plane, and J. R. McGinnis, "Teacher change following a professional development experience in integrating computational thinking into elementary science," *Journal of Science Education and Technology*, vol. 29, no. 1, pp. 174–188, 2020.

[44] M. Israel, J. N. Pearson, T. Tapia, Q. M. Wherfel, and G. Reese, "Supporting all learners in school-wide computational thinking: a cross-case qualitative analysis," *Computers & Education*, vol. 82, pp. 263–279, 2015.

[45] E. A. Davis and J. Smithey, "Beginning teachers moving toward effective elementary science teaching," *Science Education*, vol. 93, no. 4, pp. 745–770, 2009.

[46] B. Miri, B.-C. David, and Z. Uri, "Purposely teaching for the promotion of higher-order thinking skills: a case of critical thinking"*Research in science education*," *Research in Science Education*, vol. 37, no. 4, pp. 353–369, 2007.

[47] F. C. Curran and J. Kitchin, "Early elementary science instruction: does more time on science or science topics/skills predict science achievement in the early grades?" *AERA Open*, vol. 5, no. 3, 2019.

[48] C. P. Brackmann, M. Román-González, G. Robles, J. Moreno-León, A. Casali, and D. Barone, "Development of

computational thinking skills through unplugged activities in primary school," in *Proceedings of the 12th Workshop on Primary and Secondary Computing Education*, pp. 65–72, Association for Computing Machinery, New York, NY, USA, November 2017.

[49] C. Angeli and K. Jaipal-Jamani, "Preparing pre-service teachers to promote computational thinking in school classrooms," in *Computational Thinking in the Stem Disciplines: Foundations and Research Highlights*, pp. 127–150, Springer, International Publishing, 2018.

[50] P. Sengupta, J. S. Kinnebrew, S. Basu, G. Biswas, and D. Clark, "Integrating computational thinking with K–12 science education using agent-based computation: a theoretical framework," *Education and Information Technologies*, vol. 18, no. 2, pp. 351–380, 2013.

[51] K. P. Waterman, L. Goldsmith, and M. Pasquale, "Integrating computational thinking into elementary science curriculum: an examination of activities that support students' computational thinking in the service of disciplinary learning," *Journal of Science Education and Technology*, vol. 29, no. 1, pp. 53–64, 2020.

[52] A. Yadav, H. Hong, and C. Stephenson, "Computational thinking for all: pedagogical approaches to embedding 21st century problem solving in K–12 classrooms," *TechTrends*, vol. 60, no. 6, pp. 565–568, 2016.

[53] G. E. Hall and S. M. Hord, "Implementation: learning builds the bridge between research and practice," *The Learning Professional*, vol. 32, no. 4, pp. 52–57, 2011.

[54] U. Kale, M. Akcaoglu, T. Cullen, and D. Goh, "Contextual factors influencing access to teaching computational thinking," *Computers in the Schools*, vol. 35, no. 2, pp. 69–87, 2018.

[55] K. Jaipal-Jamani and C. Angeli, "Effect of robotics on elementary preservice teachers' self-efficacy, science learning, and computational thinking," *Journal of Science Education and Technology*, vol. 26, pp. 175–192, 2017.

[56] P. J. Rich, B. Jones, O. Belikov, E. Yoshikawa, and M. K. Perkins, "Computing and engineering in elementary school: the effect of year-long training on elementary teacher self-efficacy and beliefs about teaching computing and engineering," *International Journal of Computer Science Education in Schools*, vol. 1, no. 1, pp. 1–20, 2017.

[57] A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory*, Prentice Hall, 1986.

[58] J. L. Maeng, B. A. Whitworth, R. L. Bell, and D. R. Sterling, "The effect of professional development on elementary science teachers' understanding, confidence, and classroom implementation of reform-based science instruction," *Science Education*, vol. 104, no. 2, pp. 326–353, 2020.

[59] C. E. Coburn, W. R. Penuel, and C. C. Farrell, "Fostering educational improvement with research–practice partnerships," *Phi Delta Kappan*, vol. 102, no. 7, pp. 14–19, 2021.

[60] C. E. Coburn and W. R. Penuel, "Research–practice partnerships in education," *Educational Researcher*, vol. 45, no. 1, pp. 48–54, 2016.

[61] K. L. Mulvey, L. McGuire, A. J. Hoffman et al., "Learning hand in hand: engaging in research–practice partnerships to advance developmental science," *New Directions for Child and Adolescent Development*, vol. 2020, no. 172, pp. 125–134, 2020.

[62] W. R. Penuel, C. E. Coburn, and D. J. Gallagher, "Negotiating problems of practice in research–practice design partnerships," *Teachers College Record: The Voice of Scholarship in Education*, vol. 115, no. 14, pp. 237–255, 2013.

[63] D. Cadieux Boulden, E. Wiebe, B. Akram et al., "Computational thinking integration into middle grades science classrooms: strategies for meeting the challenges," *Middle Grades Review*, vol. 4, no. 3, pp. 1–17, 2018.

[64] "Bronfenbrenners Ecological Systems theory: Microsystem: Mesosystem: Ecosystem: Macrosystem," Shark Tank Updates, 2021, https://biznewske.com/bronfenbrenners-ecological-systems-theory/.

[65] H. Woltman, A. Feldstain, J. C. MacKay, and M. Rocchi, "An introduction to hierarchical linear modeling," *Tutorials in Quantitative Methods for Psychology*, vol. 8, no. 1, pp. 52–69, 2012.

[66] E. R. Banilower, "Understanding the big picture for science teacher education: the 2018 NSSME+," *Journal of Science Teacher Education*, vol. 30, no. 3, pp. 201–208, 2019.

[67] R. I. COUNT, "Policy & advocacy for rhode Island's children," 2018, Retrieved from http://www.rikidscount.org/.

[68] D. A. Dillman, J. D. Smyth, and L. M. Christian, *Internet, Phone, Mail, and Mixed Mode Surveys: The Tailored Design Method*, Wiley, Hoboken, 2014.

[69] "Spearman's rank-order correlation using SPSS statistics," "Spearman's Rank Order Correlation using SPSS Statistics–A How-To Statistical Guide by Laerd Statistics," 2018, [Online]. Available: https://statistics.laerd.com/spss-tutorials/spearmans-rank-order-correlation-using-spss-statistics.php.

[70] S. M. Hord and J. L. Roussin, *Implementing Change through Learning: Concerns-Based Concepts, Tools, and Strategies for Guiding Change*, Corwin Press, 2013.

[71] S. W. Raudenbush and A. S. Bryk, *Hierarchical Linear Models: Applications and Data Analysis Methods*, Sage Publications, Inc, 2nd edition, 2002.

[72] J. W. Creswell, *The Selection of a Research Approach. Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, Sage Publications, Inc, 2014.

[73] C. L. Plumley, *2018 NSSME+: Status of Elementary School Science*, Horizon Research, Inc, Chapel Hill, NC, 2019.

[74] S. D. Sparks, "Make science education better, more equitable, says National Panel," *Education Week*, 2021, [Online]. Available: https://www.edweek.org/teaching-learning/make-science-education-better-more-equitable-says-national-panel/2021/07, [Accessed: 8-Jan-2022].

[75] W. J. Rijke, L. Bollen, T. H. S. Eysink, and J. L. J. Tolboom, "Computational thinking in primary school: an examination of abstraction and decomposition in different age groups," *Informatics in Education*, vol. 17, no. 1, pp. 77–92, 2018.

[76] C. Chalmers, "Robotics and computational thinking in primary school," *International Journal of Child-Computer Interaction*, vol. 17, pp. 93–100, 2018.

[77] A. Nolan and T. Molla, "Teacher confidence and professional capital," *Teaching and Teacher Education*, vol. 62, pp. 10–18, 2017.

[78] A. Lakshmanan, B. P. Heath, A. Perlmutter, and M. Elder, "The impact of science content and professional learning communities on science teaching efficacy and standards-based instruction," *Journal of Research in Science Teaching*, vol. 48, no. 5, pp. 534–551, 2011.

[79] J. H. Sandholtz and C. Ringstaff, "Inspiring instructional change in elementary school science: the relationship between enhanced self-efficacy and teacher practices," *Journal of Science Teacher Education*, vol. 25, no. 6, pp. 729–751, 2017.

[80] Y. Dong, V. Catete, R. Jocius et al., "PRADA: a practical model for integrating computational thinking in K–12 education," in *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*, pp. 906–912, Association for Computing Machinery, New York, NY, USA, February 2019.

[81] M. Zhao, X.-H. Wang, and H.-L. Ma, “Promoting teaching self-efficacy in computational thinking of school teachers,” in *2020 Ninth International Conference of Educational Innovation through Technology (EITT)*, pp. 235–239, IEEE, Porto, Portugal, December 2020.

[82] W. R. Penuel, B. J. Fishman, R. Yamaguchi, and L. P. Gallagher, “What makes professional development effective? Strategies that foster curriculum implementation,” *American Educational Research Journal*, vol. 44, no. 4, pp. 921–958, 2007.

[83] Y. Yang, X. Liu, and J. A. Gardella Jr., “Effects of a professional development program on science teacher knowledge and practice, and student understanding of interdisciplinary science concepts,” *Journal of Research in Science Teaching*, vol. 57, no. 7, pp. 1028–1057, 2020.

[84] G. E. Hall and S. M. Hord, *Implementing Change: Patterns, Principles, and Potholes*, Pearson Education, Inc, Hoboken, NJ, 2020.

[85] J. H. Sandholtz and C. Ringstaff, “Offering modest supports to extend professional development outcomes and enhance elementary science teaching,” *Professional Development in Education*, vol. 48, no. 4, pp. 672–687, 2022.