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High School Science Teacher Use of Planning Tools to Integrate Computational Thinking

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ABSTRACT

In an effort to deepen learning in K-12 science classrooms, there has been a national movement to integrate computational thinking (CT). The purpose of this phenomenographic study was to understand teachers' perceptions of the function and usefulness of a task analysis and a decision tree tool designed to help them with integration. Teachers participated in a long-term professional development to improve their knowledge and application of CT and then developed lesson plans integrating CT into science investigations. To assist in the integration, teachers used the two unique tools. No one lesson plan or content area addressed all of the CT practices, but all CT practices were addressed in lessons across all four science areas. All 19 teachers found that the task analysis tool helped them to shift their lessons to a student-centered focus and helped them pinpoint data practices so they could systematically integrate CT practices. However, they expressed confusion over the amount of detail to document on the tool. Similarly, teachers found both benefits and barriers to the decision tree tool. Teachers found the decision tree tool to be useful in predicting the ways students may misunderstand a data practice and in reflecting on the level of accomplishment of students. However, teachers were sometimes uncertain with how to efficiently document complex student behaviors when engaged with data practices and CT. Implications for the use of the two lesson planning tools is discussed.

KEYWORDS

Professional development; science education; computational thinking; lesson planning; task analysis

In 2012, the National Research Council (NRC) released their framework for K-12 science education that features a three-dimensional learning design integrating disciplinary core ideas, cross cutting concepts, and science and engineering practices. As part of the science and engineering practices, the NRC recommended computational thinking (CT) be integrated into science education because computational approaches are vital to the sciences for understanding patterns and making predictions. Science and mathematics disciplines are becoming more computational through the use of computer modeling and complex computation (Bailey & Borwein, 2011; Foster, 2006; National Research Council [NRC], 2012). By teaching CT as part of the science curriculum, students will have a learning environment that more accurately models the professional nature of science and mathematics inquiry (Augustine, 2005; Weintrop et al., 2016).

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Wing (2006) demonstrated that STEM disciplines have become increasingly computational, arguing that K-12 students should engage in computational. Since that time, there has been an explosion of efforts to incorporate CT in educational systems worldwide. However, the majority of these tend to focus on teaching students how to code (Kite et al., 2021). Yet, since its reemergence in 2006, CT has been seen as a fundamental skill about conceptualizing, not programming. Wing (2006) emphasized that CT was about how humans thing rather than how computers think. Some researchers have even shown that CT does not even require computers (Berland & Lee, 2011; Lee et al., 2020; Lee & Recker, 2018), teaching CT through board games, circuits, and "unplugged" activities (Lee & Vincent, 2019). While CT has long been a part of STEM professionals' repertoire of professional skills, it has not been explicitly and systematically integrated into formative education. Perhaps it is for this reason that the NRC recommended that CT be integrated into science education.

Though there has yet to be a consensus on the precise definition of CT (Grover & Pea, 2018; Peter et al., 2021; Shute et al., 2017), there are certain practices that appear in most definitions, expanding on Wing's original proposal of abstraction, algorithms and automation. Common CT practices are decomposition, pattern finding, abstraction, algorithmic thinking, automation, and analysis (Henderson et al., 2007). *Decomposition* is breaking a complex task down into sub-processes. *Pattern finding* involves identifying recurring elements. *Abstraction* is the process of stripping away detail to create useful generalizations. *Algorithmic thinking* results in the creation of specific sequences that, when given a specific input, result in a predictable output. *Automation* is the operationalization of these processes through technology.

In short, CT is an approach to solving problems and designing systems that takes a complex problem and reformulates it into a set of smaller problems that are solvable through organizing, analyzing, representing, and automating solutions (International Society for Technology in Education [ISTE], 2011). CT and science have a reciprocal relationship where learning one can help students learn the other (Weintrop et al., 2016). As a result, integrating CT into a science classroom can deepen the learning of science (NRC, 2012).

Without proper support, integrating novel CT instruction into an established science curriculum can be overwhelming for teachers and students alike. Currently, there is little guidance and support for science teachers to integrate CT with existing content (Grover & Pea, 2013; Weintrop et al., 2016). Additionally, integrating CT into science lessons often requires a shift from a teacher-centered to a student-centered focus in the classroom, because students engage in CT practices and process skills rather than being on the receiving end of direct instruction (Grover & Pea, 2013). Research suggests that teachers need support learning CT and integrating it into their lessons.

Teaching students to think computationally has become increasingly important as high school science courses move toward data-based practices. Science educators have moved away from teaching a singular, lock-step method (i.e., the "scientific method") to instead emphasize core practices that scientists engage in dynamically and iteratively. *Analyzing and Interpreting Data* is one of the eight core science and engineering practices promoted by the Next Generation Science Standards (NGSS; NGSS Lead States , 2013). The standards explain that, "scientific investigations produce data that must be analyzed in order to derive meaning" (https://ngss.nsta.org/Practices.aspx?id=4). Working with data is far from a novel activity in science. In fact, that's the reason the NGSS emphasizes this (and other) scientific practice. Rather than encourage the teaching of science by accepting others' interpretation of pre-collected data, the practice of "analyzing and interpreting data" suggests that students themselves should be generating and interacting with data in order to inform their understanding of science. In addition, the NGSS highlights the fact that modern technological tools have made it easier for students to generate and work with data for visualization and analysis, thus promoting a computational approach to working with data in science education.

Computational tools have made the creation, collection, manipulation, analysis and visualization of data more accessible than ever before (Weintrop et al., 2016). For example, students can now use smartphones to access computational tools in lab-like mobile environments (Shabrina & Kuswanto, 2018). Freely available computational tools give students the ability to work with data to model phenomena in ways previously only available at high cost to professional scientists. Furthermore, through computational tools, students have access to data collected outside of their immediate geographies through scientific organizations that make large and small datasets available (e.g., noaa.org, data.gov). Inasmuch as data has become more accessible, teachers need to teach students how to think computationally so they can engage in data-driven inquiry. Simply working with data does not equate to data science any more than working with computers equates to computer science. Rather, as Weintrop et al. (2016) highlights, modern STEM professionals work with data in order to engage in scientific inquiry.

The purpose of this study was to examine high school teachers' perspectives about the use of two planning tools to assist in CT integration into data practices in science lessons: a *task analysis* tool used to identify opportunities to integrate data practices and CT into lessons, and a *decision tree* tool used to predict student responses to CT activities.

Computational thinking in the science classroom

As culture and industries become more automated, there is a greater need for problem solving skills and CT, which are not currently being taught explicitly in many public schools (Kale et al., 2018). Weintrop et al. (2016) analyzed 30 different high school lesson plans and drew upon prior research and interviews with experts in mathematics and science to develop four primary categories of CT integration into science: (a) data practices, (b) modeling and simulation practices, (c) computation problem solving practices, and (d) system thinking practices. Because CT has the potential to be adapted to fit any subject and taught in a manner that enhances students' ability to problem solve and think computationally (Kale et al., 2018), using CT in the classroom can offer students the opportunity to acquire skills needed to prepare them for careers in the STEM disciplines.

In this study, we adopted Weintrop et al.'s (2016) category of *data practices* for the integration point of CT integration into lesson plans which are organized into five practices: creating data, collecting data, manipulating data, visualizing data, and analyzing data (see Table 1). We selected data practices as the integration point because the teachers in the study had experience with incorporating data practices into lessons involving student investigations in science, and because CT can be used to engage in data practices (Peters-Burton et al., 2020). Therefore, in this study, we proposed strategies to teachers for integrating CT into lesson plans and explored how teachers understood and used the strategies. Table 1 provides definitions for data practices and CT practices relevant to this study.

Table 1. Definitions of data practices and computational thinking.

Data Practice	Definition
Collecting Data	Data can be collected through observation and measurement. Computational tools can assist by automating the process of gathering data, recording data, and data storage.
Creating Data	Data can be created by taking an observation or measurement, often with the assistance of computational tools like probe-ware, sensors, or cameras. Creating data can also include using computational tools to generate data involving phenomena that cannot be easily observed or measured.
Manipulating Data	Data manipulation includes sorting, filtering, cleaning, normalizing, and merging data sets in order to analyze and communicate trends. Computational tools allow larger, more complex data sets to be manipulated.
Analyzing Data	Analyzing data includes identifying patterns or anomalies, defining rules to categorize data, and identifying trends and correlations in order to make claims and draw conclusions. Computational tools make it possible to analyze larger data sets in a more reliable, effective manner.
Visualizing Data	Visualizing data involves displaying data using graphs and charts. Computational tools can be used to create these as well as more dynamic, interactive displays.
Computational Thinking Practice	**Definition**
Decomposition	Deliberately breaking down a complex problem into less complex sub-problems. Reducing the main problem into manageable steps or sub-problems.
Pattern Recognition	Identifying repeated sequences within the data.
Abstraction	Clarifying the problem by removing as much unnecessary or distracting information from the problem. Create a generalized representation of the problem/solution.
Algorithmic Thinking	Creating a series of precisely defined steps or rules used to solve a problem. Generating a structured formula that provides a predictable outcome given a specified input.
Automation	Using coding and/or technology to outsource work so that it reduces or removes the requirement for direct human action in order to achieve a desired outcome.

Data Practices as defined by Weintrop et al. (2016), p. 136.
Computational thinking practices defined by Henderson et al. (2007).

Instructional planning tools

Although there has been published work on student learning of CT, and on the potential for teachers to assist CT learning (Kite & Park, 2020), the current study is unique in examining teacher planning for integration of CT. Since there is little known about teacher planning in this context, we will review literature in this section on teacher planning activities. Teacher preparation programs emphasize the importance of instructional planning in assisting prospective teachers to become effective in designing lessons (Kitsantas & Baylor, 2001). Reiser and Dick (1996) defined lesson planning as a detailed step-by-step guide that highlights teaching objectives for what students will learn, how students will learn, and what will be accomplished during the course of the lesson. It generally consists of seven steps: (a) identifying instructional goals; (b) identifying an instructional objective; (c) planning instructional activities to employ; (d) choosing instructional media; (e) developing assessment tools; (f) implementing the instruction; and (g) revising the instruction. Practicing teachers are generally aware of and able to implement these steps when developing their lesson plans. However, most teachers need professional development in designing effective lesson plans that not only focus on content but also attempt to develop science practices (Peters-Burton & Botov, 2017). Engagement in using a variety of tools to create effective lesson plans might help teachers identify new ways to teach complex concepts in the classroom, particularly in science education (Baylor et al., 2001).

A number of instructional planning tools exist in the literature that attempt to help teachers become effective planners. For example, the Instructional Planning Self-Reflective tool (Baylor et al., 2001) was developed based on Zimmerman's (2000) model of self-regulated learning to facilitate reflective thinking during the process of lesson planning. Another tool, the Constructivist Planning Self-Reflective Tool (Baylor et al., 2001) was developed based on self-regulated learning (Zimmerman, 2000) and constructivism (Jonassen, 1999) and was intended as a learning support plan, consisting of several questions addressing three phases of the lesson planning process: before, during, and after. Further, Guskey (2005) developed a tool called the Table of Specification for teachers to add precision and clarity to their teaching. Guskey designed this tool to provide guidance for consistency among standards in an effort to assist students reaching benchmarks. To use the Table of Specifications in a manner that addresses the standards, Guskey recommended teachers ask two questions: (a) what must students learn to be proficient at a specific standard? and (b) what must students do with what they learn? Linking classroom assessment to the Table of Specification can help teachers accurately match assessment items to table components and incorporate items that address a range of skills while generating consistency and thoroughness (Notar et al., 2004). Through table development, teachers can structure key benchmarks students must reach to progress toward proficiency.

Task analysis

Another instructional planning tool, cognitive task analysis, has received recent attention in science education (Feldon et al., 2010). Task analysis was developed during the early part of the industrial revolution. Task analysis protocols allowed industrial managers to observe highly skilled workers and describe precise activities that were required to perform the variety of jobs required for manufacturing. These task analysis processes include gradual, motivated, deliberate practice that is challenging and accompanied by consistent relevant feedback over a significant amount of time results in the creation of cognitive structures that contribute directly to exceptional performance. This is the process that distinguishes novices from experts (Clark & Estes, 1996).

Cognitive task analysis is defined as the process of breaking down a skill into smaller, more manageable tasks in order to reduce the cognitive load on a learner so that they can focus on one part at a time, eventually synthesizing the parts to be proficient in the skill. This process has been used in a number of content areas to improve curriculum design and implementation such as in science education to articulate scientific inquiry skills in an undergraduate biology course (Feldon et al., 2010). Additionally, cognitive task analysis has been used to improve learning with students in special education, computer science, educational technology, and nursing (Chao & Salvendy, 1994; Clark & Estes, 1996; Clark et al., 2008; Crandall & Getchell-Reiter, 1993; Szidon & Franzone, 2009).

Decision trees

One drawback of only using cognitive task analysis is that it emphasizes expert thinking (Clark & Estes, 1996). While emphasizing expert thinking enables teachers to plan lessons that draw on proven and implicit practices, it ignores the many mistakes that novices might make. Decision Tree analysis provides a way to identify the many types of thinking or decisions students might make as they work through the lesson. In turn, teachers are then able to pinpoint and prepare for potential naïve understandings.

While these tools may help teachers to highlight otherwise ignored aspects of their lessons, a focus on cognitive task analysis and decision trees in instructional planning might be even more critical for teaching computational skills to students. Since CT skills cut across many disciplines of science (i.e. physics, chemistry, and biology), these tools may be widely used in science classrooms (Weintrop et al., 2016; Wing, 2006). In order to study how the teachers interacted with the task analysis and decision tree lesson planning tools, we asked the following question: How did teachers perceive the function and usefulness of two tools designed to help them integrate CT into high school science data practices?

Method

Research design

Phenomenography was chosen for this study because it has promise to communicate findings in a way that is suited to address educational challenges directly, particularly in science education (Han & Ellis, 2019). Phenomenography as a research design illustrates the qualitatively different ways in which people experience, conceptualize, realize and understand various aspects of a phenomenon that could be explained (Marton, 1986). In this study, the teachers' use of the two unique tools, task analysis and decision tree, to integrate CT into data practices in their science lesson plans was the focus phenomenon. Qualitative variance was examined among individual teachers for the research question since individuals may have different personal experiences with lesson planning tools. Rather than reduce results into a few generalizable categories, phenomenography highlights the varied approaches that teachers might take as they engage with tools to integrate CT into their existing lessons.

The present study uses the conceptions of learning how to use new lesson planning tools in the same way that Han and Ellis (2019) have used conceptions of learning science as a research object. By defining the research object as the use of the two tools in lesson planning for the purpose of integrating CT, the design of the study focused on the intentionality of the teachers' experiences, which first described the structural aspect of the research object (the variation among the integration of CT in lessons) and the referential aspect of the research object (the meaning that teachers perceived in using the tools to integrate CT; Han & Ellis, 2019).

Participants

Twenty in-service secondary science teachers were recruited from a school district in the mid-Atlantic region of the United States to participate in a professional development program focused on integrating CT into science lessons that featured data practices. The nineteen teachers that agreed to participate in the study (15 female, 4 male; 17 White, 2 Asian) were licensed in their respective discipline: biology (n = 9), chemistry (n = 4), Earth science (n = 2) and physics (n = 4). Their teaching experience ranged from 3 to 26 years with an average of 10.45 years.

Description of the professional development

The professional development (PD) experience consisted of a two-week summer institute in 2019, followed by monthly two-hour meetings from September 2019 to March 2020. The monthly meetings were intended to continue until May but were halted due to COVID-19 protocols. The two-week summer institute focused on learning about CT in the context of data practices in week one, and supports for students to learn about CT in the context of data practices in week two. The monthly meetings focused on improving teaching understanding of CT, further integrating CT from the summer work products, and reflecting on student performance when the lesson was taught. The overarching goal of the PD was for the teachers to work in groups so they could integrate CT into three already established lessons using the lesson planning tools.

Week one

In the first week of the PD, the teachers were introduced to the need for CT, both for themselves and for their students. Next, the concept of CT along with the components of decomposition, pattern recognition, algorithmic thinking, abstraction, and automation were defined and then reinforced as teachers engaged in hands-on activities that supported the use of CT as a cognitive tool to leverage data practices. Next, teachers learned about the concept of data practices based on Weintrop et al.'s (2016) categories of creating, collecting, manipulating, visualizing, and analyzing data. Finally, teachers analyzed lesson plans to locate and categorize data practices and then used the common lesson plan template to fill in the task analysis tool.

Task analysis tool. The purpose of the task analysis tool was to help teachers break down lessons into smaller tasks so that they could locate opportunities to integrate CT. The task analysis tool, as seen in the partial example of Figure 1, consisted of four columns. Teachers were initially instructed to fill out the first two columns of "teacher will" and "student will." Then teachers were asked to identify data practices in their lesson and mark that on the correct row in the task analysis tool. Finally, teachers were instructed to choose at least one computational thinking practice for every data practice they identified. During the PD, the researchers reviewed the teachers' task analysis and provided feedback. Teachers completed and revised the task analysis tools by either meeting as a small group and working through disagreements, or completed the tool individually and met to revise after they discussed to consensus. Figure 1 explains the first few activities of an Earth science lesson on factors that influence the height of tides.

Week two

Week two of the summer institute was focused on ways that teachers can support students in learning CT. Similar to week one, this week of the summer institute was a combination of direct instruction, small group practice, feedback, and revision of products. Teachers learned about self-regulated learning and the role of self-reflection in helping students to become more aware of their learning processes. A variety of learning strategies were introduced to the teachers, and they worked on how to articulate the learning strategies in their lesson plans while receiving feedback from the instructors. In addition to self-

Partial Task Analysis Sheet as an Example of Teacher Entries for Tides Lesson

Teacher will…	Student will…	Data Practice	Computational Thinking Practice
Lesson 1- Introduction/Hook			
Show students map of Chesapeake Bay Tunnel Bridge (video) • Can stop video at keyword (variable) and look it up Explain next task – students will be looking at 4 locations for patterns of ocean levels over one day	Explain ideas about water level change over the course of a day (knowledge model)		
Lesson 1- Activity 1 Looking for Patterns			
	Locate website http://tidesandcurrents.noaa.gov/stations.html • Software will log what will occur • Classlist (time period of when to see website) – will be visually marked for the teacher	Collecting	Automation: Tell students that they are going to create a model that will help them to predict the height of tides at different locations. They can do this using Google Sheets.
	Choose parameters and collect data from the website • Can identify what students mark • Can feed information to teacher/lab partners/self	Collecting	Decomposition: Students will break down the problem and choose which parts to focus on resolving first. Pattern-finding: Students will analyze current tide data to look for patterns that might allow them to create an accurate model.

Figure 1. Partial task analysis sheet as an example of teacher entries for tides lesson.

reflection, teachers learned about ways to motivate students and then applied the motivational strategies to science lessons. Finally, teachers applied the learning and motivational strategies to CT practices in their lesson plans using the decision tree tool.

Decision tree tool. The purpose of the decision tree tool was to help teachers tangibly plan for ways to give feedback to students who need support. The format of the decision tree tool consisted of a matrix:

- the first column of the matrix was filled out with the “student will” column from the task analysis tool only from rows that indicated data practices and CT

- the second and subsequent columns were to be filled in to describe possible ways students had errors in carrying out the task in the first column.

Teachers worked together when they planned lessons to create a decision tree for the lesson. They discussed the possible errors students could make on the task and filled in the row for that task with conceptions of possible student errors. The process of filling out a decision tree was to encourage teachers to think deeply about how a student would react to the data practices in the lesson. Figure 2 displays a partial decision tree from a biology lesson on experimental design.

Monthly content area meetings

As part of the PD, teachers attended monthly meetings for two hours with the other teachers in their content area (biology, chemistry, Earth science, and physics) and two of the paper's authors to discuss lesson planning and implementation.

Data sources

Data sources for this study were collected with a focus on the ways teachers integrated CT into their lessons and their perceptions of the process of integration. The data sources include a survey of demographic information, lesson plans and planning tools (task analysis tool as seen in Figure 1 and decision trees as seen in Figure 2) developed during the PD, individual interviews of all teachers after they completed the lesson plans, and transcripts of monthly meetings.

Teachers created lessons on a template provided at the PD (see Appendix A for the template) which included explicit instructions for student objectives, formative and summative assessments, and student activities. Each content area group of teachers were asked to produce three lessons over the course of the year of PD. All lessons were focused on student investigation of science phenomena using data and included a task analysis chart and decision tree tool. The lessons ranged in duration from one to four days. At least two teachers from each content area taught each of the lessons created in their group.

The aim of the semi-structured interview was to examine teachers' experiences and perceptions in integrating task analysis tools and decision trees into their lesson plans after they engaged in opportunities to practice and apply what they learned. A one-hour interview was conducted after the summer PD with each teacher individually. Interview questions were grouped into the following topics: motivations for teaching CT, PD planning tools, and learning about CT. An example prompt was: "When you were developing lesson plans, please explain the process you followed for integrating CT in the lesson plan." Responses were recorded and transcribed, as were the discussion during the monthly meetings.

Analysis

The central goal of phenomenographic analysis is to capture the set of qualitatively different categories representing variations of experiences amongst participants for a phenomenon (Han & Ellis, 2019). All data were collected before analysis began, allowing for iterative, rather than sequential consideration of the categories (Yates et al., 2012). Marton's (1986) process for analysis was used, which began with identifying data related to the phenomenon, *Example of Teacher Entries for Possible Student Misdirection During Tides Lesson*

Student will…	Possible Student Misdirection
Create their own driving question for lab extension and identify independent and dependent variable	• incorrectly identify dependent variable • incorrectly identify independent variable • not identify any dependent variable • not identify any independent variable
Justify why their research question is relevant and interesting to test	• question is not relevant to experiment
Students write a null hypothesis and alternative hypothesis	• incorrectly write one of their two hypotheses • incorrectly write both of their hypotheses • not write any hypotheses
Students identify constants and how many trials will be performed	• incorrectly identify constants, but correctly identify how many trials will be performed • correctly identify constants, but incorrectly identify how many trials will be performed • incorrectly identify constants and how many trials will be performed • not identify constants but do identify how many trials will be performed • identify constants but do not identify how many trials will be performed • not identify constants or how many trials
Students identify how they will summarize their data	• not identify how they will summarize their data • **have a hard time understanding that they had two different ways they could summarize their data. They could either calculate the averages or they could look at the last 30 seconds value.**
Students write new procedure to test their driving question	• write new procedure but procedure will not result in data to answer their driving question • not write procedure.
Students construct a data table to record data next class	• not construct a data table to record data next class

Figure 2. Example of teacher entries for possible student misdirection during tides lesson.

the use of the task analysis, and decision tree tools. After identification, we sorted the data into the categories of task analysis benefits, task analysis drawbacks, decision tree benefits, and decision tree drawbacks. Once sorted, the categories were contrasted for variation among the teachers, and finally the reliability was checked through interrater reliability.

Coding

All transcriptions and lesson plan artifacts were coded for any references to the task analysis tools and decision tree tools. Four a priori codes were initially used to fragment the interviews: task analysis benefits, task analysis barriers, decision tree benefits, and decision tree barriers. Once the codes were placed broadly into these four categories, they were refined line by line. Two coders fragmented the data independently. Out of 84 total utterances, there were only two disagreements, resulting in a kappa value of .98. These disagreements were discussed until consensus. The two initial discrepancies across the coders occurred in the area of barriers, particularly when an interviewee mentioned that there were no barriers. Once the data were fragmented into the four codes, excerpts were read for meaning and grouped within each of the codes to describe trends. Each researcher involved in the analysis developed their own matrix of trends and brought their groupings to a discussion. Trends were discussed until consensus was reached.

Findings and discussion

To answer the research question, How did teachers perceive the function and usefulness of two tools designed to help them integrate CT into high school science data practices?, we analyzed teacher lesson plans, planning tools, transcripts from teacher interviews, and the monthly teacher meetings. The transcripts from these data sources revealed several themes regarding benefits and barriers of both tools.

Task analysis tool benefits

The teachers reported that the task analysis tool helped them to break down complicated lessons and better understand the role of the teacher and the student, similar to the finding of Szidon and Franzone (2009). Others remarked on its capacity to help them find holes or gaps in data practices and CT in their lesson planning process, similar to the findings of Chao and Salvendy (1994) and Clark et al. (2008).

Shifting to student-centered lessons

As teachers decomposed their lessons using the task analysis tool, they filled in the “teacher does” and “student does” columns. The teachers reported that the format helped them realize that often the teacher column was filled while the student column only had few entries. As teachers reflected on their lessons as part of using this planning tool, they were able to re-design the lesson as student-centered.

LR: You’re really separating out what the teacher does versus what the students do and looking at how much teachers are controlling the process. And [I wonder] how much of it is left to them [the students] to explore? That’s always a fine line because you want them to just come to the epiphany on their own with little guidance.

The act of using the task analysis tool to break down lessons helped the teachers think about the design of their lesson with more detail and attention to individual processes. As the teacher, CK, explained,

> I found it really useful to think about how I guide kids step by step through a process. I don’t think I had really thought about some of the questions that I asked them for every single step. I think so much of what we do becomes automated because we’re just used to doing it, and we don’t stop and think . . ., this is really decomposition.

The task analysis tool initiated an iterative reflective process whereby teachers returned to their lesson plans to replace teacher actions with student actions, making their lessons more student-centered, which was also recommended by Grover and Pea (2013) as a prerequisite to integrating CT into science lessons.

Connecting data practices to computational thinking

Many teachers found the task analysis tool instrumental for making connections between data practices and CT. The tool allowed teachers to isolate data practices, in the same way that Feldon et al. (2010) found, which in turn allowed them to directly connect data practices to CT, which as teachers remarked, was empowering.

KC: Being able to identify within the task analysis [tool] where the computational thinking and data practices are. Being able to think about the two together was something that I had not done before. … Being able to identify that the lesson has those components is really empowering.

Weintrop et al. (2016) discussed the need for teachers to be comfortable teaching the material to effectively integrate CT into science lessons. Some teachers recognized that they had been applying CT generally to lesson plans, but without structure. As recommended by Weintrop et al. (2016), this tool scaffolded the teachers so that they could identify where CT practices were taking place within a specific lesson and link them to data practices.

Task analysis tool barriers

With regard to barriers to using the task analysis tool, teachers grappled with two main areas: conceptions of CT terms which inhibited their ability to link CT and data practices, and establishing the amount of detail to provide when writing the task analysis tool.

Using computational thinking terms with students

Many teachers noted that while data practices were familiar to them, computational thinking was new to them. Several teachers discussed wrestling with the ideas involved in CT.

AP: I'm always double checking because I haven't practiced [CT] as much. The task analysis tool to me is the most overwhelming step because I have very little practice with computational thinking.

MS: I was just talking with another teacher and we were both kind of joking. These terms, we still get them confused, we're still not comfortable with using them.

Unfamiliarity with CT practices and related concepts resulted in a lack of confidence about labeling a lesson component with an incongruent CT practice. This finding corroborates Clark and Estes (1996) claim that the use of task analysis requires expert thinking and reiterates the call for targeted PD experiences on CT practices and how they can be applied in science (Augustine, 2005; Kale et al., 2018; NRC, 2012; Weintrop et al., 2016; Wing, 2006).

Level of detail required

The process of breaking down lessons into teacher and student steps was met with some resistance as teachers were unsure of the level of detail to provide in the task analysis.

JC: So it was a combination of not getting too nitty gritty and going down a rabbit hole And sometimes, I think we were wondering if we broke things down too much.

CK: You could break it down to be every minute of the lesson or is it a bigger chunk? So, I think that was frustrating for me because I could spend five hours on this, making it every single tiny thing that takes place. Or I could spend two hours on this and make it more big picture, and it was hard to find the balance between that.

Teachers struggled with this new task of breaking the lesson down into manageable steps in order to pinpoint CT and data practices, while at the same time striking a balance between becoming too detailed and losing sight of the overall goal of the lesson. Although it has been demonstrated previously that task analysis of lessons can improve depth and completeness of student knowledge (Chao & Salvendy, 1994; Clark & Estes, 1996; Clark et al., 2008; Crandall & Getchell-Reiter, 1993), this can occur only when teachers are clear about the level of detail of understanding that is appropriate for the students that they teach.

Decision tree tool benefits

The decision tree was conceptualized as a tool to be used by teachers during the lesson planning process to predict the ways in which students could become misdirected when accomplishing data practices using CT. Although decision trees are not specific to CT, they were used to help teachers prepare to address as many student scenarios as possible and think deeply about this new area of instruction. In effect, it asked teachers to predict student behavior about using CT in data practices in the planning stage. There were three main themes found regarding the benefits of the decision tree tool: (a) predicting students' misdirection during the science investigation, (b) understanding student performance during the lesson, and (c) reflecting on the lesson after it was taught.

Useful in predicting student behavior

There was a large amount of evidence in the interviews that teachers found the tool useful in predicting student behavior. For example, JC said, "It forced us to think about what students will go through to the lesson and what mistakes we predict they're going to make. And how we can help them." Similarly, KC stated, "So, I think it's useful in being able to think about how to redirect students if they don't come to the right conclusion or if they don't come to the intended conclusion." The decision tree tool was a concrete way for the teachers to predict student actions, particularly when the lesson content is new to the teacher.

Useful to understand student performance

One trend that emerged from monthly meeting discussions involved differentiating lessons for students of different academic levels. In one instance, a chemistry teacher who taught advanced classes authored the lesson and two other chemistry teachers who taught regular level chemistry were concerned about the extensive vocabulary and the in-depth data analysis that required a higher mathematics level. A great deal of discussion ensued about how to modify the lesson to meet the needs of students who come to class with various levels of understanding and experience. The task analysis and decision trees tools were the focal point of the discussion and were used to record the differences.

Additional discussion during the monthly meetings focused on how to scaffold tasks within lesson plans taught in both higher and lower level classes. Teachers who worked with students in higher academic-level classes did not want their students confined to certain choices but instead wanted their students to have more freedom within the investigation. This generated decision trees with more branches documenting possible student errors and redirection.

Useful as a reflective tool

Some teachers used the decision tree as a reflective tool. Following the lesson, teachers would return to and revise the decision tree, incorporating items from their observations. Many times teachers did this in consultation with each other, generating robust documentation of student action.

KG: I'm now going back and reworking those decision trees based on what I took notes on what the students did [during the lesson]. So, what I discovered is the decision tree is exactly what I thought they were going to do on other things.

EB: I did the decision tree after [teaching the lesson], but we just met last night and had a productive discussion, all the physics teachers together, and we were able to fill it in completely. They're hitting on all these things that as a teacher I know I'm aware of and I might point out to my students, but to then document them in writing the lesson plan.

Perhaps because teachers were actively looking for and documenting student misconceptions, teachers were surprised to find that student actions did not match their predictions or expectations. One teacher, despite creating a robust decision tree, found that her students made very few missteps. Another teacher was surprised to find trends in the mistakes made by students in different academic levels. This teacher found that students in the regular chemistry class were more diligent in following scientific practices while students in the higher-level chemistry course skimmed or bypassed the way they performed scientific practices.

Decision tree tool barriers

Following the PD session and during the first few months of the academic year, there was still some uncertainty surrounding the format in which to create the decision tree. There were some issues associated with how to record what goes on in the classroom—which is a dynamic environment—and put these actions into a document that reflected student behavior. Many times, the teachers were able to document the pathway for a student who understands the concepts and practices well but were not able to predict the types of missteps or misconceptions students may have.

SI: It's hard to predict what the student will do until you've done it with students. It's hard to predict what they will do, which directions they'll go know. Until once you've done a few times and then it's easier to see what decisions are making.

ZMP: I think it is hard for a person to create a decision tree that encompasses the level of complexity of decision trees in a real classroom. So the early stages of [creating a] decision tree are tough.

HY: I think it was just confusing in the beginning like, what a decision tree is and how detailed it needed to be and then like trying to figure out all the different pathways a student might go.

Other researchers have similarly attempted to "CT-ify" science instruction by providing teachers with lesson planning tools (Bain & Wilensky, 2020). While no framework currently exists to help science teachers identify specific opportunities for integrating CT, Bain and Wilensky found that helping teachers focus on factors of time, size, number and repeatability provided clearer entrance points (or "vectors") for thinking computationally. Curiously, each of these factors focus on the data practices that teachers might use in their classes, which may be a more natural entry for teachers to incorporate CT. As our findings revealed, the practice of identifying how students will work with data and then implementing this in the classroom can be an effective tool for science teachers to begin integrating computational thinking into investigation-based lessons.

Conclusions

Many science teachers already use data practices and CT in their science lessons, but are not yet using the vocabulary associated with those practices or overtly teaching the practices. In order to use the decision tree and task analysis to effectively incorporate CT into science lessons using data practices, teachers need a solid understanding of both. Because the teachers worked together, there is evidence that using these tools in small groups helps to spur conversations about integrating CT into data practices.

Shifting to student-centered lesson and integrating CT

The process of using both tools in science lessons facilitated activity among teachers and moved them toward what the students were accomplishing and away from what the teacher was presenting. The use of the decision tree and task analysis charts gave teachers two mechanisms to discuss and decompose their own lessons, leading them to look more closely at the components. When used either to predict or reflect upon student actions, the decision tree tool helped teachers identify where student misconceptions could (or did occur during the lesson while the task analysis tool helped teachers systematically select parts of a lesson to integrate CT. Some teachers found it helpful to have one or both tools on a clipboard or mobile device while teaching the lesson, allowing them to move about the classroom and update the tools in real-time.

Differentiating lessons

Finally, teachers found the use of the task analysis and decision tree tools helpful in identifying the ways that the instruction could be differentiated for students. The tools created a space for teachers to break down their lesson and consider how students would react to their instruction. In doing so, the tools helped to illustrate areas during the lesson where more support could be given to struggling students and support could be faded for advanced students. More work needs to be done with understanding how teachers may be able to use the decision tree tool in a deeper way.

Implications for research and practice

The present findings might benefit practitioners such as curriculum designers, school administrators, and educational researchers who are interested in integrating CT in science lessons. First, the planning tools used in this study supported teacher integration of CT into science lesson plans, and assisted teachers in breaking apart lessons so that they could look deeper into the aims and objectives for each lesson "move" and clear away the noise or unnecessary parts of instruction. Second, findings showed that it was not sufficient to ask teachers to integrate CT when armed only with knowledge about CT. Teachers often need more systematic and structured support (e.g., PD) when attempting to complement existing lessons with new instruction. Further research is needed in this area to examine forms of PD that might enable teachers to infuse CT into science lessons plans. In addition, the task analysis charts and decision tree tools are one way to assist teachers in analyzing their lessons through the lens of student engagement in science investigation. It might be interesting to explore the role of technology in this process.

Limitations

Although the current research provided an initial study of integrating computational thinking into data practices using task analysis and decision trees, there are several limitations that need to be acknowledged. First, conceptions of the students are not included in this study which would have provided an additional layer of information about the functionally and effectiveness of the two tools. Second, the study was conducted in one school district and therefore findings may not be representative of other school systems around the country. Finally, it could be that more experienced teachers may infuse computational thinking into data practices differently from less-experienced teachers, which was not taken into consideration in this present study. Therefore, future studies should examine whether variables such as teacher knowledge and experience in engaging deeply with computational thinking while designing lesson plans might alleviate differences among domains.

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APPENDIX A

SPIN Lesson Plan Template

Module Summary: Identify how the project fits into the big picture, develops authentic skills, and embraces habits of mind of the discipline.

Module Science Content Topic(s):

Module Computational Thinking Practices (select all that apply)

Decomposition	Pattern Seeking	Algorithmic thinking	Abstraction	Automation

Data Practices (select all that apply)

Creating Data	Collecting Data	Manipulating Data	Visualizing Data	Analyzing Data

Strategies for students when working on independent practice outside of the classroom

Grade Level(s):

Established Goals of the curriculum: students will understand (big ideas/key knowledge), know, be able to do what (key skills)? What are the big ideas (cross-cutting themes) in the project? How does it address science and engineering practices? How does it address mathematics and language objectives?

Learning Objectives for the Lessons:

Lesson 1:
Lesson 2:
Lesson 3:

Content Standards Addressed in Lesson

State Standards of Learning

Teacher Background Information

What content does the teacher need to know about to deliver this lesson? Brief summary.

Research Question for Data Analysis: Fill in the research question that the data analysis is attempting to answer here.
Methodology for Creating Data :
Data Set(s): (actual data that was obtained from the methodology that can be used by students to answer question if the teacher does not have time to complete)
Conclusions (Scientific Argument) from Data Analysis: (how do you explain the results based upon the content knowledge students should have learned or be learning – this could be an example of an exemplary student connection between content learned and results)
Prerequisite Key Knowledge: What are the key concepts that are most important for students to know in each discipline for the unit?

Prerequisite key knowledge

Glossary of key vocabulary: Identify terms and their definitions that will be used in the lesson for each of the areas below. This shared vocabulary will help the SPIN system communicate more effectively and efficiently.

Content vocabulary
Computational thinking and data practices vocabulary
Self-regulated learning vocabulary

Assessment Plan: Define the products and artifacts for the lesson. Be sure to include a variety of assessments for learning that are closely tied to the content, learning skills and technology tools outcomes. The products and criteria must align with the objectives and outcomes for the project.

State the criteria for exemplary performance for each product. Plan for assessments that provide student feedback as the project progresses and provide for a culminating appraisal of performance or product with an accompanying rubric that clearly assesses the learning targets.

Formative Assessments	
Summative Assessments	

Lesson #1 Plan

Lesson Title:
Lesson Summary:
Lesson Science Content Topic(s):
Lesson Computational Thinking Practices (select all that apply)

Decomposition	Pattern Seeking	Algorithmic thinking	Abstraction	Automation

Lesson Data Practices (select all that apply)

Creating Data	Collecting Data	Manipulating Data	Visualizing Data	Analyzing Data

Essential Question(s): what questions will guide student learning in this lesson?
Measurable Learning Objectives: Must be measurable; give criteria and condition for student performance
Time Required:
Necessary Materials:
Safety Considerations:

Lesson Preparation
What will the teacher need to plan ahead of time for this lesson?
Lesson Plan Components
Opening Activity / Introduction (includes students' active participation and links to prior knowledge)
Teaching Activities (outline of activities, good questions to pose, major points, etc. – INCLUDE APPROXIMATE TIMES FOR ALL ACTIVITIES)
Closing Activity (includes students' active participation, reviews lesson, and relates to objective)
Task analysis of Lesson 1

Teacher will	Student will	Data Practice	Computational Thinking Practice	Metacognitive Prompt (instructional or assessment)

Lesson #2 Plan

Lesson Title:
Lesson Summary:
Lesson Science Content Topic(s):
Lesson Computational Thinking Practices (select all that apply)

Decomposition	Pattern Seeking	Algorithmic thinking	Abstraction	Automation

Lesson Data Practices (select all that apply)

Creating Data	Collecting Data	Manipulating Data	Visualizing Data	Analyzing Data

Essential Question(s): what questions will guide student learning in this lesson?
Measurable Learning Objectives: Must be measurable; give criteria and condition for student performance
Time Required:
Necessary Materials:
Safety Considerations:
Lesson Preparation
What will the teacher need to plan ahead of time for this lesson?
Lesson Plan Components
Opening Activity / Introduction (includes students' active participation and links to prior knowledge)
Teaching Activities (outline of activities, good questions to pose, major points, etc. – INCLUDE APPROXIMATE TIMES FOR ALL ACTIVITIES)
Closing Activity (includes students' active participation, reviews lesson, and relates to objective)
Task analysis of Lesson 2

Teacher will	Student will	Data Practice	Computational Thinking Practice	Metacognitive Prompt (instructional or assessment)

Lesson #3 Plan

Lesson Title:
Lesson Summary:
Lesson Science Content Topic(s):
Lesson Computational Thinking Practices (select all that apply)

Decomposition	Pattern Seeking	Algorithmic thinking	Abstraction	Automation

Lesson Data Practices (select all that apply)

Creating Data	Collecting Data	Manipulating Data	Visualizing Data	Analyzing Data

Essential Question(s): what questions will guide student learning in this lesson?
Measurable Learning Objectives: Must be measurable; give criteria and condition for student performance
Time Required:
Necessary Materials:
Safety Considerations:
Lesson Preparation

What will the teacher need to plan ahead of time for this lesson?

Lesson Plan Components

Opening Activity / Introduction (includes students' active participation and links to prior knowledge)

Teaching Activities (outline of activities, good questions to pose, major points, etc. – INCLUDE APPROXIMATE TIMES FOR ALL ACTIVITIES)

Closing Activity (includes students' active participation, reviews lesson, and relates to objective)

Task analysis of Lesson 3

Teacher will	Student will	Data Practice	Computational Thinking Practice	Metacognitive Prompt (instructional or assessment)