Jl. of Technology and Teacher Education (2022) **30**(4), 493–525

Exploring Elementary Teachers' Perceptions of Data Science and Curriculum Design through Professional Development

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Data science and computational thinking (CT) skills are important STEM literacies to help people make informed decisions in their daily lives. At the elementary level, particularly in rural areas, there is little instruction and limited research towards understanding and developing these literacies. Using a Research-Practice Partnership model (RPP; Coburn & Penuel, 2016) we conducted multimethod research to investigate nine elementary teachers' perceptions of data science and related curriculum design during professional development (PD). Connected Learning theory, enhanced with Universal Design for Learning, guided ways we assisted teachers in designing the data science curriculum to promote equity for students. Findings suggest teachers maintained a high level of interest in data science instruction and CT before and after the PD and increased their self-efficacy towards teaching data science. We present seven themes which describe how the PD assisted teachers in understanding data science and creating the curriculum and include their challenges and suggestions for improvement. Implications for elementary schools are discussed to assist other educators implement successful data science PD and curricular design.

Keywords: data science; Research-practice partnerships; elementary school curriculum; professional development; computational thinking

Developing STEM (science, technology, engineering, and mathematics) literacies and skills at an early age is important to foster long-life analytical and problem-solving skills, yet limited research exists on STEM teaching practices at the elementary level to guide educators (National Science and Technology Council, 2018). In part, this is because advancing STEM skills in elementary schools is difficult as teachers are required to teach subjects outside their preparation, have limited technology support, and may struggle to integrate and implement STEM-related computer science and engineering standards (Yadav et al. 2016). Within STEM disciplines, the rising importance of data science has heightened the need to educate the population at an early age. Data science skills and practices assist people of all ages in making informed decisions to better understand risks (e.g., exponential spread of disease, getting the best rate for a loan, decrease in pollinators) for individuals and the larger society (National Science and Technology Council, 2018). Data science is rooted in investigating "data collected from social and environmental contexts in which learners often find themselves deeply embedded" (Wilkerson & Polman, 2020, p. 1). Data science requires skills like computational thinking (CT), which harnesses the power of computing to decompose problems and analyze data towards solving open-ended problems, yet CT is new to most elementary school curricula and not widely studied (Shute et al., 2017).

Moreover, the direst need for increased STEM education and data science is in the expansive, high-poverty rural areas in the southeastern United States that are typically under-resourced (Harris & Hodges, 2018). In addition to curricular needs, there is a lack of research exploring the effect of teaching on learning in rural schools where students often experience large academic performance gaps in math and reading, and limited science instruction (Showalter et al., 2019). In rural communities, the main barriers identified with STEM instruction are lack of funding and incongruent values between local culture and economic demand, which make it difficult for educators and students to see the value of STEM (Harris & Hodges, 2018). There are research initiatives aimed at improvement, such as the Research + Practice Collaboratory (researchandpractice.org), which seeks to actively involve STEM educators at all levels in innovative teaching practices. While important, the STEM curricula are not typically developed collaboratively with teachers and may not address specific needs of the students or fully consider the context of the community (e.g., available resources, locally important issues). Additionally, STEM teaching and research has primarily occurred independent of computer or data science skill development, missing a critical opportunity for young people to develop integrated problem-solving approaches (Weintrop et al., 2016).

In sum, data science education is crucial for the health of society, yet the impact of data science education on learning among rural, elementary-aged students remains largely unexplored. In this study, we worked with rural elementary educators to co-create an integrated data science curriculum, and we elicited teachers' feedback on the curriculum. To situate our study within the literature, we review scholarship on efforts to increase data science instruction in K-12 schools including its need, current initiatives, and teachers' perspectives towards data science and CT. With limited studies on professional development (PD) specific to data science and elementary teachers, we provide an overview of similar STEM PD programs at the elementary level. We use connected learning theory (Ito et al., 2013) to guide STEM curriculum creation and implementation.

The Need to Increase Data Science Education in K-12 Schools

The increasing reliance on data and computing in everyday practices necessitates developing literate citizens who can work with data and algorithmic computational methods beginning at an early age. However, data science education for young learners, especially elementary and middle school children, rarely prepares them for this societal need (Kjelvik & Schultheis, 2019). Elementary learners acquire little to no experience with data science and usually arrive unprepared to deal with computational problems when they get to higher levels of education (Martinez & LaLonde, 2020). Studies have attributed this to students' infrequent engagement with data (Lee et al., 2021), abstract mathematics curriculum (Finzer, 2013), or teachers' lack of data science preparation hinders their ability to integrate data science practices into their lessons (Bowen, 2021; LaMar & Boaler, 2021). These literacy practices include data collection, aggregation, sorting, and classification to make data-based decisions. The relevance of data science to STEM fields also makes early education critical to ensure learners possess required problem-solving and critical thinking skills needed to solve future data-based problems (Martinez & LaLonde, 2020). Since children's interests and attitudes towards STEM domains develop during their early education, there is a need for positive educational experiences to hone their ability and increase their confidence to think critically and work with computational problems.

However, creating and implementing effective data-rich learning environments can be complex and requires collaboration between researchers, the computer science community, and educators. Including data science as another subject is not always feasible with busy teaching schedules. Because data science cuts across all disciplines, rather than creating data science as a separate subject in K-12, it makes sense to support teachers in assisting learners to develop data skills across several disciplines. Effective practices include using digital computational tools, making data more accessible, and helping learners easily manipulate and visualize data (Finzer, 2013). Honing these practices necessitates supportive resources such as PD, digital environments, curricular materials, and supportive communities of practices to successfully integrate data science into K-12 education (Martinez & LaLonde, 2020).

Initiatives to Increase Data Science Education

The growing need for data science education led to the development of initiatives aimed at training teachers to integrate data science concepts into their curriculum and enhance students' data science literacy skills. For example, researchers at Stanford University developed an online program to facilitate K-12 teachers' understanding of data science concepts and provided supporting strategies for integrating these concepts into their classrooms (https://www.youcubed.org/data-big-ideas/). A separate Introduction to Data Science (IDS) program led by the University of California Los Angeles provides PD to support local high school teachers' integration of data science practices such as data analysis and interpretation, statistical modeling, and CT into their mathematics classes (https://www.ucladsec.org/ids-in-the-media). Organizations such as the American Statistical Association also focus on developing data science PD materials for K-12 teachers and creating data challenges seek to introduce data science to young learners in fun ways (2021). While the initiatives represent growing efforts to increase teachers' integration of data science practices at the middle and high school level, others have worked on promoting K-12 data science education by developing teachers' ability to teach CT. This approach promotes solving problems in ways that can be understood and implemented with a computer, in essence helping students think like a computer scientist (Grover & Pea, 2018).

Perspectives on Computational Thinking to Teach STEM Skills

While CT is not new, it has been primarily associated with domain-specific disciplines like computer science and mathematics (Wing, 2006). The application of critical CT components such as reasoning practices, problem solving, and conceptual understanding is not exclusive to computer or science education, it cuts across a wide variety of disciplines. However, there are misconceptions among teachers who see CT as a computer science or STEM-specific construct (Good et al., 2017). For example, Rich et al. (2019) interviewed 12 elementary school teachers to investigate their understanding and integration of key CT features in mathematics and science classrooms. Findings indicate teachers were better at connecting CT to their mathematics teaching compared to science instruction, suggesting teachers' tendency to associate CT with domain-specific skills like mathematics and computer science despite CT cutting across all domains. The study also found teachers were able to connect some of their existing classroom practices to components of CT, implying while teachers may have a limited understanding of CT, they likely already engage in several strategies that embody CT such as problem-solving, critical thinking, and decomposition. Thus, researchers and educators can leverage teachers' prior understanding of CT-related concepts to develop PD experiences teachers can easily connect with.

In a similar study, Sands et al. (2018) surveyed primary and secondary school teachers in STEM and non-STEM related fields to understand how they conceptualized and embedded CT into lessons. They found teachers' generally believed CT involved using algorithms, problem-solving, and logical thinking. However, results also showed teachers had some misconceptions about what constitutes CT, with many teachers suggesting activities such as "doing mathematics" and "using Microsoft Office" are core features of CT. The study concluded teachers struggle with CT because they lack an understanding of computer operations and suggested increasing CT resources and PD to increase teachers' confidence when applying CT in their classrooms.

To help educators identify how to approach teaching CT, researchers offer several definitions and frameworks (Grover & Pea, 2013). Weintrop et al. (2016) proposed a CT-STEM taxonomy of practices to help define CT for math and science and assist researchers and educators to focus on the application of computational practices in STEM areas. The taxonomy was created by analyzing interviews with STEM professionals to identify existing real-world instantiations of CT and related practices. They also reviewed existing inventories, standards documents, and exemplary educational activities. The taxonomy consists of four strands: data practices, modeling/simulation practices, computational problem-solving practices, and systems thinking practices. In our work with teachers, we primarily used the data practices strand of collecting, creating, manipulating, analyzing, and visualizing data to help them understand the connection between CT practices and data science (see Figure 1).

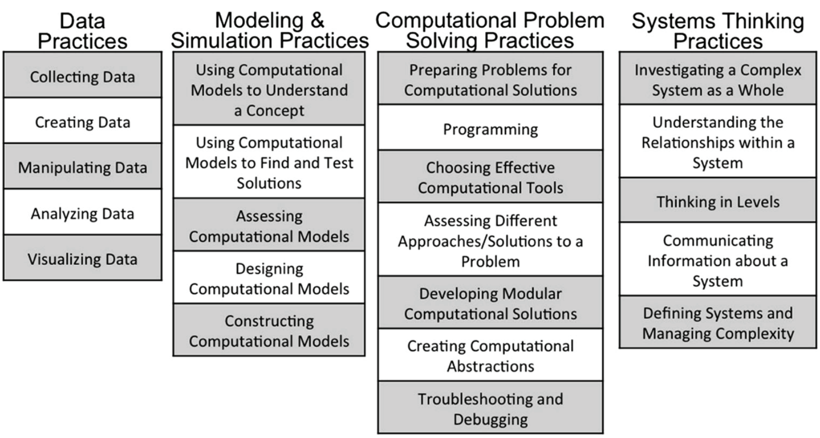


Figure 1. Computational Thinking in Mathematics and Science Taxonomy (Weintrop et al., 2016).

STEM Professional Development

For educators to effectively teach and develop STEM literate learners, they need to have a vast understanding of STEM processes. Several studies have found student STEM learning suffers when educators do not experience effective PD (Hudley & Mallinson, 2017; Mizell, 2010; Nadelson et al., 2013). What has proven effective is focusing on content and pedagogy through active learning and science practices link teaching goals with learners' experiences, and mentor or expert support (Lambert et al., 2018). For example, a multi-year study with 66 teachers explored an early career induction program intended to develop the teachers' content knowledge and teaching in STEM (Brown & Bogiages, 2019). The PD focused on classroom-based activities emphasized learners' attention to specific scientific ideas and practices. The study found engaging teachers in tasks and practice match their disciplinary focus improved dispositions towards STEM teaching.

The results are consistent with Ring et al. (2017), who designed a three-week PD program for teachers to implement integrated STEM education in a science classroom. They found significant and consistent increases in how K–12 science teachers conceptualized science knowledge and STEM integration throughout the PD. Likewise, Gardner et al. (2019) implemented a year-long PD program to improve teachers' STEM content knowledge, self-efficacy, and practice in a non-STEM school. The results show the PD did not affect the teachers' content knowledge, but they made productive changes in their classroom practices and improved their self-efficacy.

Another emerging PD model in education is Research-Practice Partnerships (RPPs), which promote "long-term collaborations between practitioners and researchers that are organized to investigate problems of practice" (Coburn & Penuel, 2016, p. 48). RPPs foster collaborative relationships between the researcher and practitioner and lend themselves to co-designing, implementing, revising, studying, and scaling educational practices. In RPPs, the intended outcomes are jointly determined by the practitioners and researchers, and cycles of continuous improvement are supported by agreed-upon rules, roles, routines, and strategies (Coburn & Penuel 2016). Documenting effective RPP's relative to strengthening STEM or data science are in their infancy, however, several benefits of RPPs based on early work and reports include higher quality research, building capacity between researchers and teachers, and increased adoption rates for interventions. Teachers participating in STEM-related RPP's report increased confidence and self-efficacy and improved classroom practices (McGill et al., 2021).

While these studies emphasize the importance of PD other scholars note teachers' experience, limited resources, availability of competent trainers, inadequate instructional and technical support are major setbacks to implementing an effective PD program (Lambert et al., 2018; Maeng & Bell, 2015). In this study, we used an RPP (Coburn & Penuel, 2016) model of PD to co-design data science units and drew on CT-STEM data science taxonomy (Weintrop et al., 2016) to help teachers understand data science knowledge and practices

Connected Learning Theory and UDL to Guide STEM Instruction

We theorize our work using connected learning theory (Ito et al., 2013; referred to as "connected learning") to guide ways to ensure more equitable participation, particularly for students not typically involved or interested in CT or data science. Connected learning suggests effective learning environments draw on personal interests and social support to overcome adversity and acknowledge an individual's contributions (Ito et al., 2013). The theory posits that educators should value the ways youth are already engaged in learning across disciplines and environments to enable "broadening access to learning that is socially embedded, interest-driven, and oriented toward educational, economic, or political opportunity" (Ito et al., 2013, p. 4). Connected learning also suggests that learning and interest are linked, and when youth are encouraged to pursue their interests, there are positive outcomes such as academic achievement, career success, and increased engagement. Connected learning attempts to address the gap between in-school and out-of-school learning by recognizing diverse pathways to build and express knowledge. In doing so, connected learning taps into the opportunities provided by technology to link home, school, community, and peer contexts of learning. It promotes supporting peer and community connections based on shared interests to strengthen learning for under-resourced or marginalized youth (i.e., rural populations, high-poverty areas, students with disabilities).

To enhance and situate connected learning in the classroom, teachers can incorporate Universal Design for Learning (UDL) principles into their instruction. UDL is an instructional framework that supports students with and without disabilities (Center on Applied Science Education Technologies, CAST, 2018; Every Student Succeeds Act, 2015). UDL provides a framework for teachers to design their instruction to assist students in engaging with and accessing the curriculum, as well as demonstrating their knowledge (Israel et al., 2018). UDL provides multiple means of engagement (e.g., student choice), representation (e.g., text, video, simulations), and action or expression (e.g., writing, drawing, video recordings).

In this project, connected learning and UDL guides the curriculum creation in two primary ways by: (1) drawing on students' interests when selecting relevant, real-world problems to solve during the design of data science curricula (e.g., issues they care about and can relate to that have a STEM/data science focus), and (2) providing learning options that mirror what students enjoy and engage in outside of school such as video production, comics or graphic novels, designing or modeling, using visual tools and connecting with peers to foster ways to find creative solutions to problems (Mirra et al., 2018).

Purpose

We developed a RPP to co-create, with teachers, an integrated data science curriculum for elementary students. In this paper, we report findings from our initial work understanding teachers' perspectives towards data science and developing a curriculum. Specifically, we address the following research questions:

Research Question 1 (RQ1): What are elementary teachers' current perceptions of data science?
In what ways do their perceptions change after participating in PD?

Research Question 2 (RQ2): How does PD assist teachers in understanding data science and creating a data science curriculum?

Research Question 3 (RQ3): What challenges and suggestions for improvement do teachers identify when creating and considering implementing a data science curriculum?

METHODS

Our research team is engaged in a three-year project funded by the National Science Foundation (NSF) aimed at understanding students' ability to develop data science skills, with a goal of helping improve the capacity of rural elementary teachers to prepare their students in data science. Our first objective is understanding the teacher's current perceptions towards data science and creating a data science curriculum. We used a multimethod research design (Plano Clark & Ivankova, 2016) to guide data collection and analysis and answer our research questions. Multimethod research is appropriate as our goal was to address each research question with different methods; our focus was not on data integration between the methods. Quantitative data were used to determine teachers' current perceptions and changes in data science literacy practices before and after the PD. Qualitative data were used to understand how the PD assisted teachers in understanding data science literacy, creating a curriculum, and identifying challenges.

Context of our Study and Research Partnership

Cooper Creek Elementary School (all names are pseudonyms) is a public STEM school in the Southeast that serves 458 students in pre-kindergarten to fifth grade. Cooper Creek is in one of the top 10-highest priority states regarding instructional and overall educational needs in rural schools (Showalter et al., 2019). The school district spans 497 square miles and encompasses several sparsely populated, mountainous areas where internet access is often unreliable. Nearly 20% of the population lives below the poverty level. There are 23 teachers, 2 administrators, 2 instructional coaches, 9 specialist teachers (e.g., virtual education, music, physical education), 1 guidance counselor, and 1 special educator. The school's population includes 68 Black students, 86 Hispanic students, 258 White students, and 46 students who identify as multi-racial. Of those students, 455 (99%) are eligible to receive free lunch. The student-teacher ratio is 14.8 students to one teacher.

The participants include 9 teachers (1 male and 8 females) between the ages of 24-45. They taught at the same elementary school in various roles (see Table 1). Participants were recruited by the research team through their principal. Teachers were not required to participate, but all expressed an interest in learning more about data science and volunteered. The research team consists of two professors specializing in Learning Sciences, a professor of Quantitative Methods, a professor of Special Education, and three graduate students. As part of a multi-year funded study aimed at offering data science curricula for elementary students in rural populations, the research team worked with Cooper Creek teachers in grades three, four and five, to co-create a data science curriculum for their students. We purposely selected upper elementary educators to ensure alignment with the CT-STEM data science curriculum and state standards.

Table 1
Demographics of Teachers During Data Science PD

Name	Race/ Ethnicity	Years of Teaching (Years of teaching at Cooper)	Role	Subject/Current Grade	Degree(s) & Certification
Jenny	White	21 (17)	Reading Coach	Reading coach for general education teachers/ PreK-5	Master's, Bachelor's, Teaching Certificate, Admin & Leadership
Lisa	White	16 (2)	Instructional Coach	Instructional coach for general education teachers/PreK-5	Master's, Bachelor's, Admin & Supervision
Riley	White	18 (18)	General education teacher	Virtual Teacher and Science/3rd and 5th	Master's, Bachelor's, Teaching Certificate, Educational Leadership
Catherine	White	23 (1)	General education teacher	Math/4th	Master's, Teaching Certificate, Technology in Education
Lonnie	White	5 (3)	General education teacher	Reading and social studies/4th	Master's, Bachelor's, Teaching Certificate, Project Based Learning
Catie	White	11 (2)	General education teacher	Science and writing/4th	Master's, Bachelor's
Charla	Black or African American	3 (3)	General education teacher	Science/ 5th	Teaching Certificate
Annie	White	2 (2)	Specialist	Music PreK-5, Gifted & Talented 3-5th	Bachelor's, Teaching Certificate, Music K-12
Tiffany	White	16 (3)	Technology Specialist	Computer Science/ PreK-5	Bachelor's, Master's

Note. PD = professional development

CT-STEM Pop-Ups Procedures

The participants met with our research team during spring meetings (Phase 1) and attended the full duration of the summer PD (Phase 2). During the summer PD, the research team worked closely with the participants to co-create grade-level data science units. We referred to the units as CT-STEM Pop-Ups to acknowledge the focus on CT practices and STEM, but also to reference the customizable and portable nature of the curricula. In education, "pop-ups" typically refer to opportunities to engage in new material or activities not covered in the traditional curriculum through interactivity and hands-on and discovery learning, and as such are increasingly used in STEM-focused, design and engineering environments (Tranquillo & Matthew, 2015)

The first phase of this project explored teachers' perspectives and understanding of data literacies and related practices (CT and UDL) before their data science unit development. We collected data from participating teachers during three spring meetings (held online due to Covid-19 school site limitations) which occurred after school, for an average of 60 minutes per meeting. The meetings were held in January, February, and March of 2021. We administered the pre-survey during the spring meetings and focused on understanding the teachers' context, student population, and instructional needs. For example, prior to each meeting, the research team shared an agenda (via Google Drive) which contained ice breaker/opening activities. Then during the meeting, the researchers and teachers would comingle in breakout rooms where they discussed various topics to help understand each other's experiences and context. In this way, we built trust while discussing the research project and data science unit.

The second phase of this project included an intensive summer PD (see Table 2). The 25-hour PD focused on an introduction to data science software for young children within a workshop format, identifying student interests, writing data literacy problem scenarios, and incorporating universal design for learning (UDL; CAST, 2018). UDL is a flexible framework that argues for offering multiple means of engagement, representation, and expression to reduce barriers and maximize learning opportunities for all learners (Rose & Meyer, 2006). During the PD, we provided a UDL workshop to increase understanding of ways to promote equity during students' learning activities (Chardin & Novak, 2021). To increase teachers' understanding of how UDL could be implemented in the context of the data science unit we (a) defined UDL and provided several examples of ways to integrate it in CT-STEM Pop-Up instruction based on the CAST (2018) website (https://udlguidelines.cast.org/), (b) used reminder tags of UDL strategies on the unit plan template, and (c) asked teachers to highlight their intentions for UDL integration when showcasing their final unit plans on the last day of the PD.

Table 2
Overview of Daily Activities During Data Science PD

Day	Session	Activities	Resources Used
1	Morning	Goal setting, agenda review Data science workshop	Tuva; shared docs Google Drive
1	Afternoon	Identifying student's interests Scenario Writing; teacher work time	CT-STEM Pop-Up Template
2	Morning	Embodied data science activity UDL Workshop	Chart paper, post-it notes, UDL Websites Google Slides
2	Afternoon	Rotating workshops Teacher worktime	TinkerCad, Pixton, video creation tools CT-STEM Pop-Up Template
3	Morning	Standards alignment, formative and summative assessments	Assessment examples CT-STEM Pop-Up Template
3	Afternoon	UDL Review Teacher worktime	UDL website; CT-STEM Pop-Up Template
4	Morning	Authentic Assessments review; Creating Pop-Up checklists for students	CT-STEM Pop-Up Template
4	Afternoon	Teacher worktime and unit showcase	

Note. CT = computational thinking; DS = data science; UDL = universal design for learning

Participants were introduced to a simple data science cycle (clean, understand, and communicate the data), engaged in embodied data science activities, and used a web-based data visualization tool called Tuva (tuvalabs.com/) to manipulate and explain data. With limited interactive data visualization tools for elementary students to use, Tuva was chosen as it appeared kid-friendly, included several free datasets to use or modify, and had existing curricular examples to draw on. The teachers also participated in rotating workshops focused on graphic novels/comics, TinkerCad (https://www.tinkercad.com), and video creation to interest children in further exploring a data science problems and augment learning activities. We developed a simple data science framework (see Figure 2) that guided the teachers planning of daily activities throughout the unit and were subsequently used for unit plan template headings (see Figure 4 and 5). At the end of four days, the teachers co-created data science units with our team that were aligned with state standards and included performance-based formative and summative assessments.

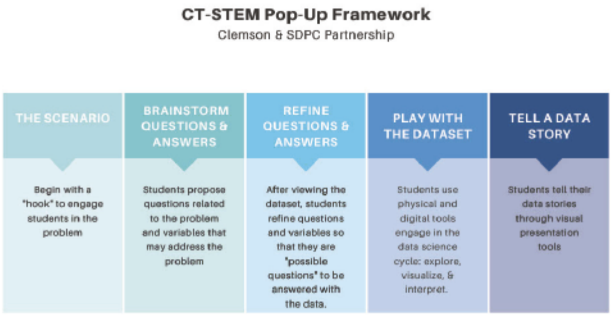
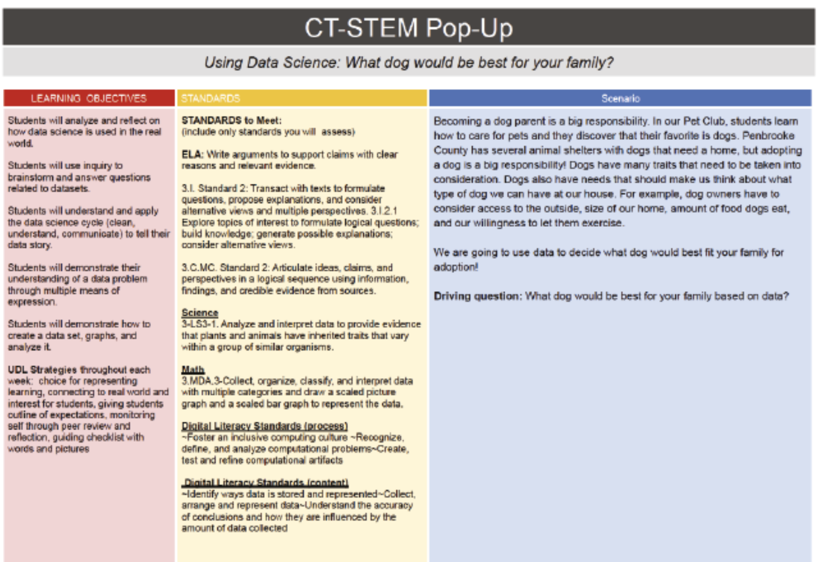


Figure 2. Data Science Framework to Guide Unit Development and Implementation.

With the support of our research team, teachers planned to implement the curriculum (we define the curriculum as all units collectively) in the fall. Figures 3, 4 and 5 are screenshots of an abbreviated co-created unit (all units were 9-10 days) using the CT-STEM Pop-Up Template to guide development. The units were intentionally integrated with existing disciplinary standards and content, and the teachers and researchers agreed the data science cycle, activities (digital and non-digital) and assessments could best be addressed in a 9-10 day unit that augmented the everyday curriculum.

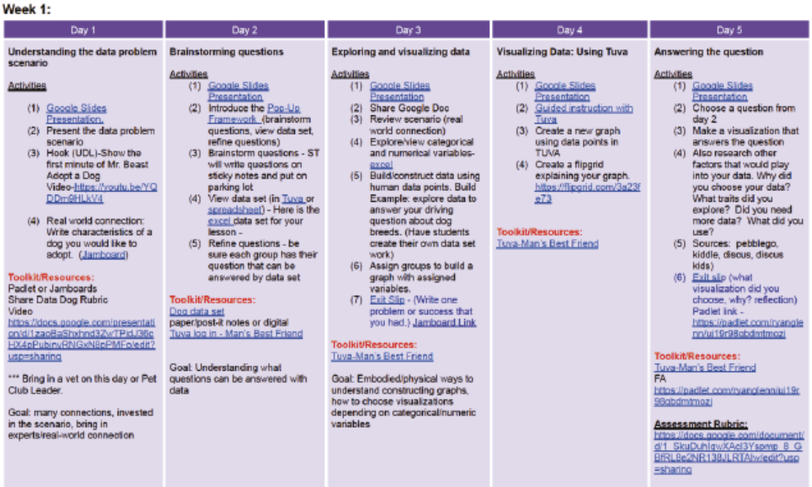


CT-STEM Pop-Up

Using Data Science: What dog would be best for your family?

LEARNING OBJECTIVES	STANDARDS	Scenario
Students will analyze and reflect on how data science is used in the real world. Students will use inquiry to brainstorm and answer questions related to datasets. Students will understand and apply the data science cycle (clean, understand, communicate) to tell their data story. Students will demonstrate their understanding of a data problem through multiple means of expression. Students will demonstrate how to create a data set, graphs, and analyze it. **UDL Strategies throughout each week:** choice for representing learning, connecting to real world and interest for students, giving students outline of expectations, monitoring self through peer review and reflection, guiding checklist with words and pictures	**STANDARDS to Meet:** (include only standards you will assess) **ELA:** Write arguments to support claims with clear reasons and relevant evidence. 3.I. Standard 2: Transact with texts to formulate questions, propose explanations, and consider alternative views and multiple perspectives. 3.I.2.1 Explore topics of interest to formulate logical questions; build knowledge; generate possible explanations; consider alternative views. 3.C.MC. Standard 2: Articulate ideas, claims, and perspectives in a logical sequence using information, findings, and credible evidence from sources. **Science** 3-LS3-1. Analyze and interpret data to provide evidence that plants and animals have inherited traits that vary within a group of similar organisms. **Math** 3.MDA.3-Collect, organize, classify, and interpret data with multiple categories and draw a scaled picture graph and a scaled bar graph to represent the data. **Digital Literacy Standards (process)** ~Foster an inclusive computing culture ~Recognize, define, and analyze computational problems~Create, test and refine computational artifacts **Digital Literacy Standards (content)** ~Identify ways data is stored and represented~Collect, arrange and represent data~Understand the accuracy of conclusions and how they are influenced by the amount of data collected	Becoming a dog parent is a big responsibility. In our Pet Club, students learn how to care for pets and they discover that their favorite is dogs. Penbrooke County has several animal shelters with dogs that need a home, but adopting a dog is a big responsibility! Dogs have many traits that need to be taken into consideration. Dogs also have needs that should make us think about what type of dog we can have at our house. For example, dog owners have to consider access to the outside, size of our home, amount of food dogs eat, and our willingness to let them exercise. We are going to use data to decide what dog would best fit your family for adoption! **Driving question:** What dog would be best for your family based on data?

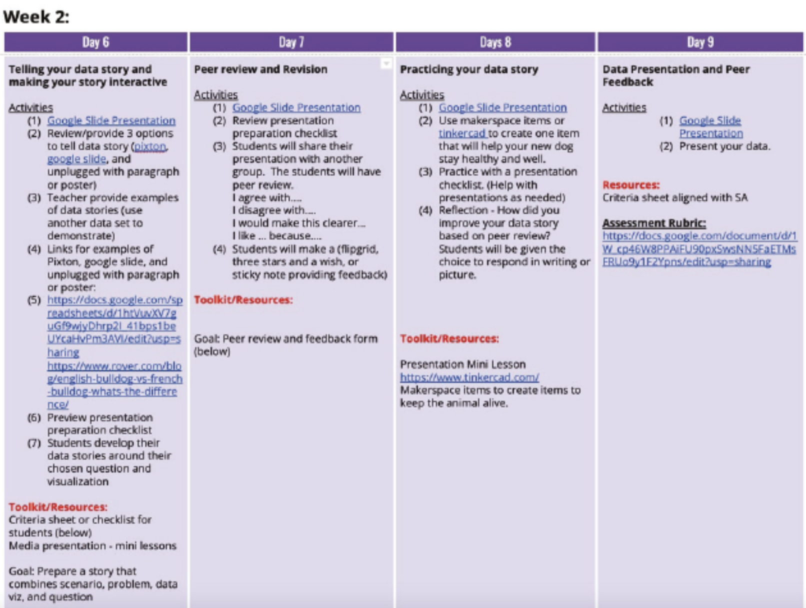
Figure 3. Screenshot of Template to Guide Unit Development.



Week 1:

Day 1	Day 2	Day 3	Day 4	Day 5
Understanding the data problem scenario Activities (1) Google Slides Presentation. (2) Present the data problem scenario (3) Hook (UDL)-Show the first minute of Mr. Beast Adopt a Dog Video-https://youtu.be/YQDDm9HLkV4 (4) Real world connection: Write characteristics of a dog you would like to adopt. (Jamboard) Toolkit/Resources: Padlet or Jamboards Share Data Dog Rubric Video https://docs.google.com/presentation/d/1zaoBaShxhnd3ZwTPidJ36cHX4pPubinvRNGxN8pPMFo/edit?usp=sharing *** Bring in a vet on this day or Pet Club Leader. Goal: many connections, invested in the scenario, bring in experts/real-world connection	**Brainstorming questions** Activities (1) Google Slides Presentation (2) Introduce the Pop-Up Framework (brainstorm questions, view data set, refine questions) (3) Brainstorm questions - ST will write questions on sticky notes and put on parking lot (4) View data set (in Tuva or spreadsheet) - Here is the excel data set for your lesson - (5) Refine questions - be sure each group has their question that can be answered by data set Toolkit/Resources: Dog data set paper/post-it notes or digital Tuva log in - Man's Best Friend Goal: Understanding what questions can be answered with data	**Exploring and visualizing data** Activities (1) Google Slides Presentation (2) Share Google Doc (3) Review scenario (real world connection) (4) Explore/view categorical and numerical variables-excel (5) Build/construct data using human data points. Build Example: explore data to answer your driving question about dog breeds. (Have students create their own data set work) (6) Assign groups to build a graph with assigned variables. (7) Exit Slip - (Write one problem or success that you had.) Jamboard Link Toolkit/Resources: Tuva-Man's Best Friend Goal: Embodied/physical ways to understand constructing graphs, how to choose visualizations depending on categorical/numeric variables	**Visualizing Data: Using Tuva** Activities (1) Google Slides Presentation (2) Guided instruction with Tuva (3) Create a new graph using data points in TUVA (4) Create a flipgrid explaining your graph. https://flipgrid.com/3a23fe73 Toolkit/Resources: Tuva-Man's Best Friend	**Answering the question** Activities (1) Google Slides Presentation (2) Choose a question from day 2 (3) Make a visualization that answers the question (4) Also research other factors that would play into your data. Why did you choose your data? What traits did you explore? Did you need more data? What did you use? (5) Sources: pebblego, kiddle, discus, discus kids) (6) Exit slip (what visualization did you choose, why? reflection) Padlet link - https://padlet.com/ryanglenn/uj19r98gbdmtmozi Toolkit/Resources: Tuva-Man's Best Friend FA https://padlet.com/ryanglenn/uj19r98gbdmtmozi Assessment Rubric: https://docs.google.com/document/d/1_SkuDuhlqwXAcl3Yspmp_8_GBfRL8e2NR138JLRTAlw/edit?usp=sharing

Figure 4. Screenshot of Week 1 of Co-Created Unit in Template.



Week 2:

Day 6	Day 7	Days 8	Day 9
Telling your data story and making your story interactive Activities (1) Google Slide Presentation (2) Review/provide 3 options to tell data story (pixton, google slide, and unplugged with paragraph or poster) (3) Teacher provide examples of data stories (use another data set to demonstrate) (4) Links for examples of Pixton, google slide, and unplugged with paragraph or poster: (5) https://docs.google.com/spreadsheets/d/1htVuvXV7guGf9wjyDhrp2I_41bps1beUYcaHvPm3AVI/edit?usp=sharing https://www.rover.com/blog/english-bulldog-vs-french-bulldog-whats-the-difference/ (6) Preview presentation preparation checklist (7) Students develop their data stories around their chosen question and visualization Toolkit/Resources: Criteria sheet or checklist for students (below) Media presentation - mini lessons Goal: Prepare a story that combines scenario, problem, data viz, and question	**Peer review and Revision** Activities (1) Google Slide Presentation (2) Review presentation preparation checklist (3) Students will share their presentation with another group. The students will have peer review. I agree with.... I disagree with.... I would make this clearer... I like ... because.... (4) Students will make a (flipgrid, three stars and a wish, or sticky note providing feedback) Toolkit/Resources: Goal: Peer review and feedback form (below)	**Practicing your data story** Activities (1) Google Slide Presentation (2) Use makerspace items or tinkercad to create one item that will help your new dog stay healthy and well. (3) Practice with a presentation checklist. (Help with presentations as needed) (4) Reflection - How did you improve your data story based on peer review? Students will be given the choice to respond in writing or picture. Toolkit/Resources: Presentation Mini Lesson https://www.tinkercad.com/ Makerspace items to create items to keep the animal alive.	**Data Presentation and Peer Feedback** Activities (1) Google Slide Presentation (2) Present your data. Resources: Criteria sheet aligned with SA Assessment Rubric: https://docs.google.com/document/d/1W_cp46W8PPAiFU90pxSwsNN5FaETMsFRUo9y1F2Ypns/edit?usp=sharing

Figure 5. Screenshot of Week 2 of Co-Created Unit in Template.

Data Sources

Surveys

To assess their self-efficacy and interest in teaching CT and data science, and perceptions of UDL, each teacher completed a survey before and after the PD. The survey was originally developed to assess elementary school teacher's self-efficacy and attitudes toward STEM (Friday Institute, 2012). We adapted the survey to focus on CT and data science. Additionally, we included items to assess teachers' perceptions of utility and personal knowledge of UDL (CAST, 2018). Individual items were on either a 4- or 5-point Likert scale (e.g., strongly disagree – strongly agree, never – always). The initial survey (pre-survey) was administered on the first day of the PD and served as a baseline for teachers' perceptions and knowledge of CT, data science, and UDL. The final survey (post-survey) was identical to the pre-survey; it was administered five days later at the end of the PD and was used to measure changes in these attributes.

Observations

An observation protocol was used to collect data on the daily interaction among participants and researchers during the PD, including documenting when/how teachers sought support from peers, shared their perspective, or engaged researchers for feedback. The observation protocol included brief descriptive information about the physical space and activities (i.e., procedures, goals, tools, technologies, materials used), and narrative portions to note the teachers' design choices (i.e., What data science problem was chosen? How did they refine or clean the data?) as well as challenges encountered while completing curriculum design activities. There was also space for the observer to write a daily reflection of what worked well, and what needed clarification or improvement.

Reflective Journal Prompts

To measure how they perceived the PD, their knowledge of CT, and reflect on their daily learning experience, participants completed a reflection journal at the end of each day during the PD. Since we adopted an RPP approach, participants were also asked to reflect on the co-design process, and whether they felt prepared to implement their CT-STEM Popup units.

Group Interviews

At the end of the PD, participants were randomly divided into two groups and engaged in group discussions that captured how the PD experience impacted their knowledge of CT, confidence in developing CT-STEM Popups, and ways they integrated disciplinary standards and addressed learners' needs. We also asked about the potential benefits and challenges of implementing the CT-STEM Pop-Ups in their classrooms. We divided participants into two groups to make the interviews conversational in nature and allow for more voices to be heard.

Artifacts

Each participant completed a CT-STEM Pop-Up unit, and the research team took photos each day to assist in documenting the process. These were used as secondary data sources to understand how teachers externalized the PD knowledge and experiences, and how they planned to apply CT-STEM knowledge during Pop-Up implementations.

Data Analysis

Quantitative Analysis

To analyze survey responses, Likert items were numerically coded 1 – 4 and 1 – 5 for 4- and 5-point scale items, respectively. Item responses were then summed to produce scale scores for each teacher and each attribute of interest (e.g., CT self-efficacy, UDL knowledge). With the pre- and post-survey scale scores, we calculated gain scores () to examine how teachers' perceptions changed after the PD. Finally, we used descriptive statistics to summarize the results. Inferential tests were not included because of the small sample of teachers and non-normal data.

Qualitative Analysis

Three members of the research team independently conducted an intensive reading of all qualitative data creating memos of participants actions and statements (Charmez, 2003) related to understanding and describing the curriculum co-creation process. The team met to discuss initial, broad patterns in the data and reach agreement to guide a priori and open coding. Next the data was imported into Maxqda (https://www.maxqda.com/) software for organization and further analysis. We used a thematic analysis in which we did a second reading of the qualitative data, beginning with transcribed interviews, reflective journals, and observations, drawing on the a priori codes from our memos to code and categorize all data and note emergent codes. Data were coded and triangulated across data sources until reaching saturation (Saunders et al., 2018). During the analysis our team met several times to compare and winnow codes, discuss and form categories, and reach consensus (Cascio et al., 2019). The categories were then analyzed and developed into themes. Finally, the artifacts were analyzed as secondary sources to better understand how the teachers created their data science units during the PD. Table 3 shows our themes with representative examples of our coded data.

Table 3

Themes and Representative Examples of Coded Data

Theme	Source: Coded Data
Demonstrating the data science process	Observation: Jenny created a comic to “hook” the kids and found a separate smaller dataset so that what is used as an example is different from what will be used for class activities. She plans to have them communicate their data story with Google Slides.
	Group interview: They are really into asking their own questions, they form ownership of their learning (Referring to having students ask questions about data.)
Sharing expertise and workload	Group interview: What was effective is seeing how we don’t know this process is having all the experts in the room that could come and help us like when you got stuck.
	Journal reflection: The research team guides you to where you need to be and gives support/help as needed. They give ideas, suggestions, and feedback through the whole process of writing the pop-up with together.
Considering design choices together	Group interview: They are interested in social media…. but there are some in our project they haven’t heard of. Like Pinterest. Their parents might not be on Pinterest. They might not have Twitter. We built in some activities throughout the week that would introduce them to those things.
	Group interview: We really went back to our standards. And because we are doing 3rd grade, we felt that it had to be simple.

Theme	Source: Coded Data
Recognizing the importance of differentiating and extending opportunities for students	Journal reflection: The approaches that I feel will appeal to my students are opportunities for inquiry, collaboration, using technology, hands on activities, and games.
	Group interview: I'm going to hopefully find a music producer or sort of similar career to just, like, kind of talk. I would love to have time for students to ask questions and send him some questions, or her, so they can, umm, so that they could answer them in a video.
Fostering feelings of confidence to successfully teach data science	Group interview: I do like how they gave us a piece only kept building upon it. So, for me, that does help.
	Journal reflection: I liked working together - learning with and from each other. I always felt like I could ask questions without judgement from the team.
Identifying challenges	Group interview: Like making sure we were staying within that realm and finding that dataset-that was another challenge.
	Group interview: Sometimes it was challenging, integrating reading, writing, and social studies, because that's what I need to teach. I mean, we obviously figured it out it as you know.
Suggestions to improve PD and curriculum creation	Group interview: If you guys could provide maybe a few extra datasets. Maybe, you can't meet everybody's needs. Like, you didn't know what we were going to do. But I think it would have helped since we saw, like I know there was only one or two I could use. But if I would have been able to see example data….
	Journal reflection: Next time, I would recommend giving teachers a checklist/specific list of what exactly needs to be in the pop-up. Even though we did an example and worked through some ideas, I didn't realize step-by-step everything that needed to be in my pop-up until day 3.

FINDINGS

We address each research question beginning with the quantitative findings. The qualitative findings are addressed in seven separate main themes that emerged from our analysis; we acknowledge some overlap between the themes.

RQ1: What are elementary teachers' current perceptions of data science? In what ways do their perceptions change after participating in PD?

Participating teachers demonstrated a high and sustained interest in teaching data science and CT. More specifically, teachers' survey responses indicated a high level of interest in teaching data science and CT before the PD (M = 37.0/50, SD = 3.5), and we observed minimal change after the PD (M = 39.1/50, SD = 4.6). For teacher self-efficacy, however, we observed substantial changes before and after the PD. For CT teaching self-efficacy, teachers initially demonstrated a moderate level of self-efficacy (M = 24.9/40, SD = 7.9), but showed a higher level of efficacy after the PD (M = 31.3/40, SD = 4.6). Similarly, for data science teaching self-efficacy, teachers' initial scores (M = 21.4/35, SD = 6.2) were lower than their post-PD scores (M = 26.6/35, SD = 4.2).

With respect to perceptions of UDL knowledge and utility, teachers demonstrated substantial gains over the course of the PD. For perceptions of UDL knowledge, teachers initially demonstrated a moderate level of UDL knowledge (M = 35.9/52, SD = 6.3), and a higher level of UDL knowledge after the PD (M = 47.7/52, SD = 4.2). For perceptions of UDL utility, teachers initially perceived UDL to have high utility (M = 44.3/52, SD = 8.1), and this increased after the PD (M = 49.8/52, SD = 4.3). Besides data science and CT teaching interest, which was initially very high, the observed pre- and post-assessment differences indicate moderate to large gains in CT and data science teaching self-efficacy and perceptions of UDL knowledge and utility. The survey results for all attributes are displayed in Table 4.

Table 4

Pre- and Post-survey Descriptive Statistics of Teacher Perceptions

Attribute	Pre-PD Mean Score	Post-PD Mean Score	Difference
CT Teaching Efficacy	24.9	31.3	6.4
DS Teaching Efficacy	21.4	26.6	5.5
CT/DS Teaching Interest	37.0	39.1	2.1
UDL Knowledge	35.9	47.7	11.8
UDL Utility	44.3	49.8	5.5

Note. CT = computational thinking; DS = data science; UDL = universal design for learning; PD = professional development; item responses were summed for each attribute to produce scale total scores.

RQ2: How does PD assist teachers in understanding data science and creating a data science curriculum?

Theme 1: Demonstrating the Data Science Process

All nine participating teachers discussed the effectiveness of using a data science framework and template to help define data science and provide a model to create their curriculum. The teachers believed that embedding the data science problem within a relevant scenario where students could brainstorm and refine questions, play with the data, and tell their story would be effective for instruction. They suggested this framework enhanced their own understanding of the data science cycle (clean, understand, and communicate the data), and would likely be appealing to their students. This was evidenced in discussions and journal reflections where they noted how they learned about data sets to pose a real-world problem and thought it would engage their students. Teachers reflected saying things such as, "I learned about data sets and was able to build them out within a lesson plan", and "Today, I learned how to use Tuva and the data sets within it", and "I loved the framework and presenting materials this way. Kids will love numbers when tied to things they are interested in."

In final reflections describing their completed unit, all teachers talked about using their topic (pet adoption, social media, popular music, water usage) to encourage students to explore data, ask questions, use Tuva to analyze and visualize the data, and present their story using a variety of digital options. This quote from Anna exemplifies a typical response:

> My module is designed to have students analyze musical elements from popular songs from the past decade (2010-2019). My students will be acting as music producers and will have to pitch their idea for a hit song to a local musician. Their pitch must be data-driven and their conclusions on what makes a popular/successful song will be drawn from the data of popular songs. I will be using Tuva for visualization of data, but also doing some unplugged activities creating data graphs. I will also be using Jamboard for collaborating, Flipgrid for some checkouts, and exit slips for checkouts as well. For creating their data story that they share, they will have a choice of using google slides, creating a video, or creating an infographic (digital or on paper).

The teachers didn't explicitly or holistically reference the CT-STEM taxonomy of practices (Weintrop et al., 2016), and we did not expect them to, but they talked about their experiences collecting or finding data as both difficult and important. For instance, the fourth-grade teachers located and cleaned social media demographic and survey statistics from five popular social networks to create usable data sets for their students to manipulate and analyze. They practiced creating data visualizations and discussed how they would engage their students in similar activities during the unit. They frequently referenced creating and manipulating data with unplugged activities built into their units (e.g., post-it notes, paper) and online software (Tuva). They also created opportunities for students to analyze and visualize data in different ways (e.g., various graphing or charting techniques, using infographics). They believed emulating similar practices during their unit would strengthen the connection between CT practices and data science for their students. In the artifact analysis we noted that every CT-STEM unit encompassed activities for students to collect, explore, ask questions, and visualize the data, and attempt to answer the unit question by telling a data story.

Theme 2: Sharing Expertise and Workload

The teachers developed an understanding of data science and created a curriculum aligned with their standards by sharing the expertise and the workload with one another and the research team. We noted them asking questions and seeking feedback from the research team and one another in daily observations, and their reflections and interviews repeatedly pointed to how they shared ideas and the workload. The sharing of expertise and workloads occurred in three different ways: (1) teachers viewed themselves as co-designers and partners with the research team; (2) they perceived the different expertise of the research team (special education, data science, curriculum design) as key to helping them create effective data science units; and (3) they shared expertise (technical, disciplinary, design ideas) with one another. In reflections and group interviews regarding working with the research team, teachers indicated things such as "they gave me great ideas and truly did co-plan the unit with me" and discussed, "working together as a team" and "feeling comfortable to ask and answer questions", one teacher said, "But I always felt like I was a colleague rather than you guys were up here" (gesturing with hands above her head).

The teachers overwhelmingly believed the make-up of the research team was key to helping them understand data science and develop their units. For example, the fourth-grade teachers discussed how one research team member helped them find a dataset that young children could visualize, while two others helped them write a good scenario and align it with standards, and the researcher with special education expertise offered advice on how the students might use themselves as part of the data set related to social media behavior.

This excerpt from a group interview sums up the sentiments towards the research team's expertise:

> I appreciated that they all had different backgrounds, and that way they would help us when we were stuck. Having people in special ed and in general ed and all of them having a background in science kind of helped us determine our products.

Regarding sharing expertise with one another, we observed teachers discussing technologies they currently used in their classrooms, sharing ways to make interdisciplinary connections with their data science problem, or ways to use physical movement and unplugged (offline) activities. We also heard them discussing ways to embed formative assessment in the curriculum and showing one another how to use portions of Tuva. They often shared the workload by designing a complementary portion of the unit taking the lead in their area of expertise. For instance, the virtual teacher was recognized for his expertise with using technologies and helped the team embed student-centered technologies in the unit. We observed one team dividing the workload where one member created a comic as a hook for the kids' scenario and found a smaller data set, while the other two team members created Google Slides to guide the daily activities and added standards. Two fifth grade teachers worked closely together to integrate science, social studies, and technology standards based on their prior experiences and expertise, eventually creating a data science unit on water conservation that integrated several collaborative technologies. One teacher commented that the co-design process, "is a design that lets all people flourish and share his or her expertise,", and another teacher described co-designing the curriculum as, "working collaboratively with other professionals to create a project…. You are utilizing your strengths, but also encouraging each other through your weaknesses."

Theme 3: Considering Design Choices Together

The teachers chose to collaboratively design their data science units in grade level teams, and this impacted their design and content choices. For example, the third grade team presented a data science problem related to choosing the best dog for a family based on data. The team collaborated to incorporate educational standards and design activities (e.g., creating a 3-D model of a structure to house the animal based on the outcome of the students' data analysis). One teacher planned to teach the unit entirely online and offered ways the face-to-face teachers could integrate similar technologies; however, the overall unit design and daily pacing was jointly determined. One exception was a music teacher who joined a grade level team but ultimately designed her own unit to address standards and content for her music classroom.

Meeting state standards was clearly important to the teachers and coded more than 60 times throughout the interviews, reflections, and observations. This was unsurprising as offering the unit during the regular school day, versus after school, necessitated planning for disciplinary integration and standards-based instruction. The need to meet state standards during the time of year the units would be implemented influenced the teachers' topic choices and ways they collaborated. Teachers relied on their primary disciplinary expertise (i.e., math, science, English Language Arts, technology, or music) when considering topics, discussing options, and dividing work.

The other design choice each team made was based on their collective perceptions of student interests and relevance, which was often related both to requisite standards and disciplinary content to cover. For example, the fourth-grade team discussed their students' interest in social media before settling on a data science problem related to using data to decide and individual's most useful social media platform. The team then went back to the fourth-grade math, English Language Arts, and social studies standards and decided to integrate them and co-teach the unit. Throughout the week, several teachers reflected on ways they addressed students interests in their design choices saying things like "I think it's important to give them something they are interested in that could lead to a career", or "We chose social media because it's applicable to students' lives." When referring to an extension activity where students could choose to tell their data story through a comic, another teacher said, "my students will absolutely adore reading comics/graphic novels. Many of my students are strong artistically and very creative, so this will be an opportunity for them to express their learning."

Theme 4: Recognizing the Importance of Differentiating and Extending Opportunities for Students

A clear theme that emerged across data sources was the importance of differentiating instruction for students through UDL and extension activities. Our research team intentionally offered workshops on UDL and asked teachers to consider integrating it their units. We also built-in opportunities to try digital tools such as Pixton (comic creator), TinkerCad (digital modeling), and video creation to help tell the students' data stories and demonstrate different skills and ways of knowing.

In general, teachers believed they were already doing some UDL practices, but as one teacher pointed out, "we just called it something else." Another discussed the importance of being intentional in the curriculum design to "reach all students in different ways". Many used the term "accessibility" when talking about the importance of offering data science learning opportunities that would appeal to all students. During group interviews several teachers discussed UDL to "level the playing field", "make it fair and accessible," and "give options and provide scaffolding" when teaching data science literacies. In group interviews and reflective journals, every teacher commented on the need to listen to students and offer them choices to engage them in learning.

Teachers wrote in their reflective journals about plans to use UDL and extension activities. One said, "We are allowing them to use a variety of tools to represent their data story." Another commented on the PD that day, saying:

> We discussed UDL, a framework for lesson planning to make learning accessible for all students. I love the incorporation of this framework into data science. We added more choice and engagement to our plans after the UDL workshop.

Theme 5: Fostering Feelings of Confidence to Successfully Teach Data Science

We noted that the PD engendered feelings of confidence in that the teachers believed they could successfully implement the units effectively in their classroom. They commented on the excitement of learning something new - referring to the data science framework, software and new technologies, while also building on previous knowledge and practices that could be paired with these new ideas. Several teachers indicated their feelings of confidence came from comfort in asking questions and feeling that they were treated as equals in the learning process. For example, one teacher reported, "you build upon our strengths and knowledge and connected it to this (referring to data science) which is helpful". During reflections and group interviews, every teacher discussed their current classroom use of UDL, and then many of them said that the UDL workshop simply reminded them to be more intentional.

Similarly, some teachers talked about using familiar technologies (i.e., Flipgrid, Google Slides, Padlet) as formative assessments or to encourage learning. It appeared that connecting the new curriculum to some of their current practices with UDL and commonly used technologies made them feel that they could more easily integrate the data science units. One teacher said, "for me the CT-STEM Pop-Up has been really good because it takes things that we were already doing, and it put it together in a beautiful place for me."

Another observed their feelings of success came from "the peer interaction, the resources that we were given along the way, the questioning, the constant questioning, and then going back to look at what we have done to work on where we are going." Another teacher commented, "I really thought everything that we've done is effective" when referring to completing a unit they could successfully implement.

RQ3: What challenges and suggestions for improvement do teachers identify when creating and considering implementing a data science curriculum?

To help other educators successfully create data science units we briefly highlight teachers' perceptions of challenges and suggestions to improve the PD, which may alleviate future design and implementation concerns.

Theme 6: Identifying Challenges

Teachers identified several challenges during the PD, and perceived challenges when considering future implementation. First, finding and cleaning data was a noted challenge from eight of the nine teachers. The free version of the software allowed for limited age-appropriate data sets, therefore our team had to help teachers locate and clean some of their own data sets. Three teachers initially found using the software difficult. Many teachers thought it was challenging to understand the data science framework through exploration versus explicit instruction on how to teach the data science cycle. A few teachers perceived learning the framework and content as a lot of steps to understand and apply during a relatively short PD. In turn, they believed they would need to simplify similar instructions for their students.

Several teachers expressed concerns about going through a new curriculum at the same time their students would experience it. A few teachers were worried about the pacing of the nine-day curriculum and whether they built in too much or too little time. The third-grade team worried that numerical data might be difficult for their students who had only "ever looked at categorical data". They planned to use primarily bar charts and break instruction down into shorter time periods to not overwhelm the students.

Theme 7: Suggestions to Improve PD and Curriculum Creation

Teachers offered many insightful suggestions to improve the PD and process of creating the data science curriculum including: (1) less discovery and more explicit instruction when using the data science software; (2) access to additional data sets without having to search for them; (3) carefully examining a completed unit before creating their own; (4) seeing a mock-up of a final student product (the data story); (5) more information about UDL and the data science framework before, versus during, the PD; and (6) checklists and rubrics for teachers to use when creating their unit, similar to what students would receive, to clarify expectations and know if the unit was "on target". A couple teachers also suggested video recording the workshops (UDL and technology extension activities) so they could replay them later.

DISCUSSION AND IMPLICATIONS FOR PRACTICE

This study reported findings from initial phases of an RPP to co-create, with teachers, an integrated data science curriculum for students at a rural elementary school. Our partnership resulted in co-created data science units for grades three, four, and five and a music classroom. Teachers within this study had little to no prior experience in data science literacies but were interested in understanding it and learning ways to effectively develop the literacies in their students. As evidenced by the survey results, this interest did not wane after the PD, rather, it remained high. Offering curricular materials and supportive PD allowed us to help teachers hone data science literacies and practices that may, in turn, be successfully integrated into their classrooms (Martinez & LaLonde, 2020).

Akin to McGill et al. (2021), the process of co-creating data science units through a RPP model proved to be an effective way to increase teachers' self-efficacy as demonstrated by the quantitative results and ways in which teachers discussed sharing expertise among one another and the research team. Similar to Coburn and Penuel's (2016) assertion, the collaborative partnership built capacity between the researchers and teachers to co-design data science units and research the process; it offered a benefit to both parties. In this case, it also built increased capacity to understand and support data science literacies *between teachers* who shared and understood a common context – the reality of standards-based instruction and the culture within their rural population. This is a significant implication for elementary schools who wish to design or revise similar data science curricula as focusing on standards is paramount for the success of many curricular innovations if offered within the school day.

Similar to findings from other STEM PD research, engaging teachers in tasks and practices that matched their disciplinary or interdisciplinary focus appeared to improve their dispositions (Brown & Bogiages, 2019). This was evident in their sustained interest in teaching data science and CT demonstrated in pre- and post-quantitative measures as well as the substantial increase in self-efficacy to teach data science and CT after the PD. We saw this in their design choices (discipline and standard-focused) and noted it in their discussions and reflections wherein they expressed comfort and confidence in drawing on some familiar practices, technologies, and resources while learning something entirely new (data science). This echoes prior research findings suggesting a need to build a supportive community of practice that is multifaceted and includes PD, curriculum, digital environments, and data science knowledge (Martinez & LaLonde, 2020).

While designing their units, we saw teachers readily engage in CT-STEM data practices (Weintrop et al., 2016) as they collected and analyzed data about themselves, located and cleaned data from other sources, discovered different ways to visualize data using digital and non-digital resources, and explored different tools for telling data stories. We noted how often the teachers discussed what they deemed developmentally interesting or appropriate for their students in manner that aligned with connected learning (Ito et al., 2013) as a starting point for developing their units. Student interest and relevance was at the forefront of many design choices, discussions, and reflections in this study. The emphasis on writing relevant problem scenarios, UDL, and extension activities to further encourage student expression and interests was apparent in design decisions and the final units. The importance of helping their students feel successful was echoed in ways the teachers in this study felt successful – by drawing on familiar technologies and experiences and building on them to increase data science literacies. The teachers planned to draw on students' prior knowledge for data science topics and activities, but also relied on what students knew and cared about when giving them learning and presentation choices. This finding, drawing on prior knowledge and familiar or preferred experiences to foster success, is encouraging as it indicates a commitment to making data science relevant to their learners (Koirala & Bowman, 2003) and may assist young children in identifying or choosing STEM pathways. In the next phase of this study, we will investigate whether the UDL and extension activities incorporated in the units are fully implemented.

Based on the survey results, the teachers demonstrated a gain in CT teaching self-efficacy after the PD. However, a noted absence in the qualitative data were teacher's direct references to CT. While teachers talked about data practices aligned with the CT-STEM framework (Weintrop et al., 2016) and we observed them connecting their disciplinary practices to components of CT-STEM data practices strand, like Rich et al. (2019) they appeared to primarily connect CT to math practices (using Tuva, graphing etc.). A clear oversight on our part during the PD was not explicitly naming, defining, and connecting CT across disciplines, or overtly increasing the understanding of CT beyond domain-specific skills. Our focus on the data practices strand limited their knowledge to some extent. Intentionally connecting CT within data science practices and across disciplines may clear up misconceptions, increase teacher confidence, and ultimately improve student outcomes.

Along with being more intentional in defining CT, the successes and challenges noted by our participants will assist in improving the next PD and co-design slated for summer, 2022. To that end, we plan to strike a balance between direct instruction and exploration with TUVA, locate additional datasets in advance, offer some reading and resources before the PD, and create more data story examples and checklists for teachers.

Limitations

We acknowledge several limitations with this study. First, our sample size was relatively small and lacked diversity, although it represented teachers in the larger school district. Second, teachers were motivated to participate as they taught in a STEM school and had extensive project-based learning experiences which may impact the results related to interest and self-efficacy. Third, while we used UDL as one way to differentiate instruction and offer student choices in how they could engage, represent, and express their learning in multimodal ways, our focus on UDL during the unit co-design was broad. This may have translated to cursory understandings of UDL instructional practices, and thus in teachers' increased perceptions of its utility and personal knowledge after the PD. Our research team is working to deepen teachers' understanding of sustained, integrated UDL practices during implementation and in future data science curricula creation.

Acknowledgements

This research is supported by NSF Award 2031175: Inclusive Data Science Education for Rural Elementary Students: A Research Practice Partnership for Agile Learning

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