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Bop or Flop?: Integrating Music and Data Science in an Elementary Classroom

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ABSTRACT
The importance of data literacies and the shortage of research surrounding data science in elementary schools motivated this research-practice partnership (RPP) between researchers and teachers from a STEM elementary school. We used a narrative case study methodology to describe the instructional practices of one music teacher who co-designed a data science curricular unit during a summer professional development program and implemented it in her 5th-grade music classroom. Data collected for this study include in-person and video observations, reflective journals, artifacts, and interviews. Findings suggest that this teacher integrated data science literacies into her classroom by supporting multiple avenues for data storytelling and relying on learners' everyday discourse and experiences. Our study details a practical example of implementing data science with non-STEM domains in elementary classrooms.

KEYWORDS
Data science; data storytelling; elementary education; research-practice partnerships; STEM; teacher professional development

Introduction

MS. HOUSTON STOOD at the front of her music classroom and presented a data science scenario to her fifth-grade students as they sat on individual carpet squares:

> The music industry is a multibillion-dollar business; the most popular songs make the most money. Everyone listens to music and has favorite songs, but only a few hundred songs a year make it to the top of the charts. **What makes a popular song successful?** You are a music producer looking to craft your next hit with a popular musician from the Greendale area. After looking at data on the top Spotify songs from the past 10 years, you are going to pitch an idea for the next hit song to the musician! In order to make a good pitch and convince the musician to work with you, you must use the data to decide what makes a song successful and popular!

Over ten days, students worked collaboratively to investigate a data science problem, "What elements need to be considered when writing and producing a popular song?" Throughout the unit, they posed questions related to the data science scenario, explored datasets based on the music industry, talked with a sound engineer about his data skills and career, refined their questions, and showcased their learning by telling a data story. Ms. Houston was one of nine teachers who worked in a research-practice partnership (RPP; Coburn & Penuel, 2016) with our research team to co-develop data science curricular units and explore ways to increase data literacies for rural elementary students.

With the increasing importance of data science to help people make informed decisions in their daily lives, developing data literacies at an early age fosters life-long analytical and problem-solving skills (National Science & Technology Council, 2018). Data literacies include the ability to comprehend, analyze and interpret data and their visual representations (Shreiner, 2018) and are

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necessary for everyday transactions to evaluate information (Kjelvik & Schultheis, 2019). Bowen and Bartley (2020) argue that data literacies are critical in assisting people in deciding how to vote, policies to support, arguments to adopt or dismiss, and products to buy.

Researchers are addressing issues bordering on the most appropriate time for students to learn data science, what to learn, the optimal arrangement of content, and the path that helps build the best foundation (Drozda et al., 2022; Lee & Wilkerson, 2018). At the elementary school level, Drozda et al. (2022) suggest a focus on developmentally appropriate competencies in statistics, data structure, modern data applications, data collection, organization, measurement, and distribution. To gain relevant skills and practices, students should be able to apply these competencies to situations such as using data to make informed decisions, relying on statistics for data analysis and visualizations, reflecting on data collection and production, how data are used for security, prediction, and automation, and data issues around privacy, ethics, and social justice (Rubin, 2020).

The importance of data science has led to conversations about developing new standards at national and state levels. However, scholars argue whether data science should be integrated across all content areas rather than being taught separately (Drozda et al., 2022; LaMar & Boaler, 2021). Whether integrated within existing subjects or presented as a separate subject, a common point of agreement is that there is a need for new data science standards in K-12 education to prepare students for a world increasingly dependent on data (Mike, 2020). In turn, national and statewide standards have been revised to integrate data science competencies. For example, mathematics topics like distribution, variability, informal measures of center, categorical data, and data collection are building blocks for data science education (Boaler et al., 2019; Boaler & Levitt, 2019). In addition, portions of the Next Generation Science Standards (NGSS) emphasize data science practices such as analyzing and interpreting data, using mathematics and computational thinking, collecting, recording, and sharing observations, and using digital tools (Drozda et al., 2022). In California, the Mathematics Framework for California Public Schools (2022) was revised to include data science concepts, including data for understanding, defining data, and representing, and interpreting data. Likewise, Pre-K–12 Guidelines for Assessment and Instruction in Statistics Education (GAISE II) has also emerged as providing guidelines to teach statistical thinking and the use of real-world data to help students develop an understanding of statistics as a tool for exploring and understanding the world around them (Bargagliotti et al., 2021). The increasing visibility of data science competencies in K-12 standards and teaching signifies data science as a valued area of study. The integration into standards is a valuable tool in helping teachers integrate data science concepts into their teaching (Lehrer & Schauble, 2000).

Data science education is prevalent in high school and higher education classrooms. However, few studies that have explored data science for elementary students. The few examples include Lee and colleagues (Lee et al., 2016; Lee & Drake, 2013; Lee & Thomas, 2011) study in which they designed and evaluated programs in which fifth grade students analyzed their movement data by creating graphs in school. Others have designed and tested digital and non-digital data visualization tools for elementary-school aged children (Alper et al., 2017; Bae et al., 2021; Bishop et al., 2020). While these recent studies have improved our understanding of data science education, more research is needed for integrating data science learning for younger students in school environments. Early elementary learners have little experience with data science and are usually unprepared to deal with computational problems when they get to higher levels of education (Martinez & LaLonde, 2020). Moreover, early elementary teachers have little experience with data science, which affects their ability to integrate data science practices into their lessons (LaMar & Boaler, 2021).

To better prepare students for the data literacies they will require in everyday life, scholars argue that using authentic datasets contextualized to what students care about is an engaging way to have them think critically about data (Kjelvik & Schultheis, 2019). Developmentally, elementary school children need background knowledge, interest in, and a general understanding of the topic at hand to make the data set and visualizations relevant as they move from concrete experiences to more abstract learning (Alper et al., 2017). Children who have opportunities to explore their interests, collect their data, or explore "messy" real-world datasets, are often better at data interpretation than those who learn from more "sanitized" datasets from textbooks (Bowen & Bartley, 2020).

Interpreting data can also be described as *data storytelling* in which learners create and narrate their completed visualizations while explaining the 'what' and 'why' of their analysis (Wilkerson et al., 2021). In data storytelling, students benefit by communicating their stories to a broader audience while considering the implications of their analysis. Such stories harness the true power of data by taking facts and figures and bringing them to life through engaging multimodal means (Vora, 2019). Data storytelling is appealing for all learners, particularly young children, who often thrive on imaginative and visual stories. Motivated by calls to expand data literacies to elementary classrooms and limited research on integrated data science into everyday practices, our research draws on using authentic datasets and data storytelling to extend knowledge about integrating data science in early classroom settings.

This article provides an example of how data science knowledge and practices can be integrated into elementary school curricula using data storytelling. We narrate one teacher's data science instructional story, drawing on her experiences co-designing and developing a data science unit during summer professional development (PD) and subsequently implementing the unit in her music classroom. Narrative case study methodology illustrates how she applied data science instruction in her music classroom, including the flow of her daily lessons, strategies she employed, and revisions she made while teaching the unit. The findings in this study inform elementary educators on how to integrate data science into their classroom instruction. This case builds on our prior research detailing nine elementary teachers' perceptions and experiences when co-designing the data science curricula (Arastoopour Irgens et al., 2023; Herro et al., 2022). Our research question guiding this case is, "How does an elementary school teacher implement data science in a music classroom?"

Theoretical foundations

Socio-constructivist approaches and repertoires of practice

We theorize our work using a socio-constructivist approach to teaching and learning (Vygotsky & Cole, 1978). Socio-constructivist theories recognize the independence of social and individual processes to construct knowledge (Dahms et al., 2007) and the importance of connecting students' experiences with domain content by drawing on culture, language, and everyday practices to build literacies (Gutiérrez et al., 2009). Gutiérrez and Rogoff (2003) argue that learning occurs when students' background experiences and interests are acknowledged and encouraged during the learning process. They propose moving from focusing on students' individual traits to repertoires of practice within communities to honor various ways people learn. Nasir et al. (2005) suggest that both teaching and learning are cultural processes shaped by communities when engaging in intentional practices using tools, social networks, and discourse the community members value. Learning and development are thought to occur over one's lifespan in "diverse repertoires of overlapping, complementary, or even conflicting cultural practices" (p. 489). The scholars describe repertoires of cultural practices that youth engage in between home, school, and community activities shaping their perspectives and values and bolstering learning. Similarly, Rosebery et al. (2010) argue that situated repertoires of practice, built on the diversity of human experiences and discourse practices, particularly from non-dominant cultures, allow for the construction of shared meaning and deeper learning in heterogeneous populations. In their study of third and fourth-grade students learning about heat transfer as a scientific concept, they deliberately encouraged science talk around everyday practices, used visible structures and familiar phenomena (such as posters and ice cubes), and encouraged blending simulated and real-world activities to bridge in- and out-of-school practices. As a result of honoring students' heterogeneity, opportunities for learning increased.

When teachers facilitate instruction, encourage students to engage in social and collaborative practices, and use cultural repertoires to communicate and create artifacts, students engage deeply in learning. Leveraging the power of cultural repertoires, teachers can expose learners to real-world datasets that are aligned with students' everyday experiences and integrate the teaching of data science content knowledge and practices with students' everyday discourse.

Research–practice partnerships in education

Research-practice partnerships (RPPs) are long-term collaborative efforts between practitioners and researchers to solve educational problems and improve school outcomes (Coburn et al., 2021; Leary, & Severance, 2018). This form of partnership robustly addresses educational problems by allowing educational researchers to partner with practitioners who can implement real-world change (Potter et al., 2021). RPPs adopt a locally driven and collaborative approach to solving educational problems by developing the capacity of teachers, administrators, district officials, and communities to confront and address challenges that are specific to their contexts (Coburn et al., 2021). RPPs are dynamic in nature, and their meaning is shaped by the interaction and activities of those engaged in the partnership (Arce-Trigatti, 2021). Every RPP has distinct features that differentiate it from other RPPs, and these features are often determined by the purpose, stakeholders, and location of the partnership (Donovan et al., 2021).

As a recent report indicates, education RPPs in the US "have moved from existing as a handful of isolated partnerships to a developing field—a community of diverse individuals and organizations with shared commitments to support local educational efforts through engagement with research" (Farrell et al., 2021, p. 29). Such partnerships have made significant contributions to the field of education (Coburn et al., 2021) and have proved successful in informing real-time educational decision-making, developing sustainable curricular materials and infrastructures, addressing educational inequities, improving literacy and STEM learning, and teachers' professional development. Unfortunately, not all RPP endeavors thrive, and it is sometimes difficult to sustain long-term relationships due to power dynamics, changing policies, evolving priorities, and paucity of research funding. Coburn and Penuel (2016) argued that unique features of effective RPPs that make them distinct from other forms of partnerships include their long-term nature, the focus on problems of practice, mutual or shared authority, and the analysis and dissemination of data in a transparent and timely manner (Leary, & Severance, 2018). For RPPs to be successful, researchers and practitioners must be able to answer questions that pertain to the affordances, constraints, infrastructure, and criteria for success in the partnership (Donovan et al., 2021).

Similarly, Potter et al. (2021) noted that effective communication, trusting relationships, and power sharing are critical to the long-term success of RPPs. Researchers, teachers, and district leaders must meet regularly to negotiate the project requirements and share findings. This long-term nature of RPPs allows partners to develop trusting relationships and provide adequate time to address complex problems (Potter et al., 2021). The engagement of teachers in the co-design of materials and the dissemination of findings also serve as a relationship-building tool for developing trust and fostering dialogue among the collaborating stakeholders (Potter et al., 2021; Rorrer et al., 2021).

In this study, our RPP included building trusting relationships and a community of practice over several years (Arastoopour Irgens et al., 2023), researchers and teachers co-designing curricular units and new data visualization for implementation in their classrooms (Arastoopour

Irgens & Herro, 2023; Herro et al., 2022), and making plans for the sustainability of these curricula over time.

Using computational thinking to engage children in data science

Working collaboratively with teachers to co-design curricular materials, we draw on Weintrop et al. (2016) CT-STEM Taxonomy of Practices grounded in STEM professionals' real-world everyday practices involving computational thinking (Figure 1). The taxonomy was created with teachers, curriculum developers, and other STEM professionals who helped identify common skills and practices central to CT and characterize real-world instances of CT and related practices. 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 emphasize the connections between CT practices and data science.

Using data storytelling to engage children in data science

Another tool for engaging young learners in modern data science practices is data storytelling, which is becoming increasingly critical for communicating and functioning in society (Kahn & Jiang, 2021). When telling data stories, the presentation of data and statistical patterns is accompanied by narrative structures and media elements such as text and pictures that help to explain the analytical decisions and processes that inform the results (Wilkerson et al., 2021).

Davenport (2013) described several elements of telling stories with data. Data stories have a strong narrative and are usually driven by an objective or problem, and the findings are presented in a way that the audience will understand. Telling stories with data often concludes with actions to take and predicted consequences of those actions. Data stories seem especially appropriate for young learners as one can imagine how children might learn through narrative structures, multimodal presentations, simple concepts depicted by graphic displays and by making predictions.

Matei and Hunter (2021) argue that a good data story often violates expectations by uncovering unexpected patterns within a dataset and generating new conversations. Similarly, Knaflic

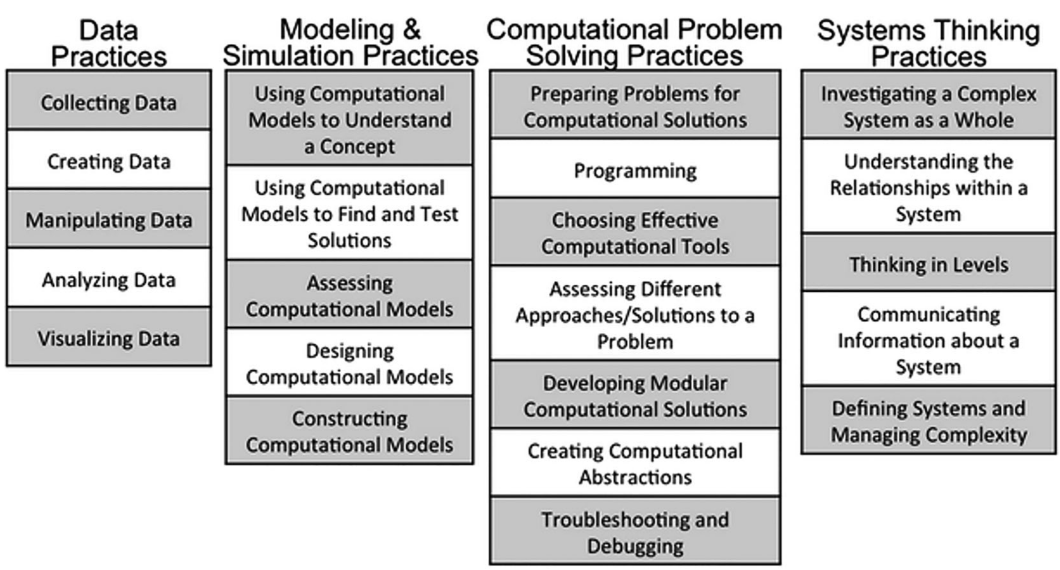

Figure 1. Computational thinking in mathematics and science taxonomy (Weintrop et al., 2016).

(2015), in his book Storytelling with Data: A Data Visualization Guide for Business Professionals, emphasized six key lessons in telling a story with data, they include: (1) Understand the context; (2) Choose an appropriate visual display; (3) Eliminate clutter; (4) Focus attention where you want it; (5) Think like a designer; and (6) Tell a story. He proposed that by adding data to stories, we extract meaningful insights from them and bring the story visually and contextually to life. These key lessons emphasized for business professionals telling data stories could be applied to K-12 education.

Although data science teaching is new to most elementary schools, some studies have examined how young students reason with data in relevant ways connected to their personal lives through data storytelling. For example, Wilkerson and Laina (2018) examined how middle school learners repurposed public data to investigate and tell stories about issues facing their communities. Learners were presented with multiple local datasets reflecting familiar but complex events they were likely to encounter daily. The learners examined patterns in the datasets based on their experiences and developed questions to be explored by combining or repurposing these data. At the end of the study, learners presented written stories and visualizations that answered their proposed questions. Results of the study showed that young children could reason with data, especially when the data were relevant to their immediate environment. The scholars argued that educators can create opportunities for integrating data modeling and exploration into existing curricular materials by presenting data to allow learners to locate themselves within the data and by providing opportunities for sharing data stories across different groups.

In a design study with middle and high school students, Kahn (2020) investigated how learners used large-scale geographical datasets to explore questions about family geobiography and told stories about their ancestral migration, cultural identities, and future self. The study found that engaging learners in explicit activities related to their personal or community lives created new data exploration, modeling, and storytelling opportunities. In a similar study, Kahn and Jiang (2021) presented a group of teenagers with a large socioeconomic dataset. They investigated how they used the data to explore their family histories and tell counterfactual stories about the socioeconomic trends of their communities. The study found that young learners could reason with data and engage in complex comparative modeling primarily shaped by their personal experiences. Studies with young children have also explored how data storytelling can be supported using web-based interactive computational tools like Story Builder (Wilkerson et al., 2021), Social Explorer (Kahn, 2020), and Gapminder (Segel & Heer, 2010) that allow learners to interact with data, transform data, create temporal annotations, and compare multiple visualizations options.

Methodology

Research context and partnership

In this study, we developed an RPP where we collaborated with teachers to create interest-based, locally relevant data science problems for students. Our research team includes two Learning Sciences professors, a Quantitative Methods professor, a Special Education professor, and four graduate students. As part of a multi-year funded study aimed at offering data science curricula for elementary students in rural populations, we worked with nine teachers in grades three, four, and five to co-create a data science curriculum for their students.

Riverside Elementary School (all names are pseudonyms) is a STEM school in the southeastern United States serving 458 pre-kindergarten to fifth-grade students. Riverside is in a rural area, which in the US consists of open countryside with population densities of less than 500 people per square mile and places with fewer than 2,500 people (Cromartie, 2019). Riverside is also part of the US's public free education system that serves children in nearby communities. There are 23 teachers, two administrators, two instructional coaches, nine specialist teachers (e.g., virtual education, music, physical education), one guidance counselor, and one special educator. The school serves diverse students from multiracial backgrounds, including 68 Black students, 86 Hispanic students, 258 White students, and 46 students who identify as multi-racial. Over 99% of students participated in the free and reduced-priced lunch as part of the national school lunch program, a proxy measure of socio-economic status. The student-teacher ratio is 14.8 students to one teacher. Written consent was obtained from all teachers and the parents of all children participating in the study. Verbal assent was obtained from children. The Institutional Review Board approved this study at the participating University.

In phase one of our research, teachers worked with researchers during a 4-day summer PD focused on an introduction to data science for young children. We assisted teachers in identifying student interests and writing data problem scenarios. Teachers 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. The teachers also participated in rotating workshops focused on using graphic novels/comics, Tinkercad (tinkercad.com), and video creation to help children further explore data science problems and augment learning activities. Over four days, the teachers co-created "CT-STEM data science pop-up" units which were customizable with flexible content and activities (Tranquillo & Matthew, 2015). The pop-ups were aligned with state standards and included performance-based formative and summative assessments. Subsequently, the units were implemented over 8-10 days in the fall of 2021. In prior studies related to phase one, we investigated the process of co-creating the curriculum with the teachers and increases in their knowledge and confidence in teaching data science (Arastoopour Irgens et al., 2023). In this second phase of our research, we focus on the data science unit implementation and rely on case study methodology to describe and analyze one teacher's experience. In this case study, we highlight one teacher, Ms. Houston, who participated in the larger study with eight other teachers. Ms. Houston is a third-year elementary music teacher who works with pre-kindergarten through fifth-grade students. She taught the data science unit in nine class periods for seven weeks in one fifth-grade class. Building on existing literature in data science education, the research team developed the data science framework (Figure 2) as a foundation for co-designing curricular units with the teachers during the summer PD.

Unit creation and instructional methods

During the 4-day summer PD, Ms. Houston worked with researchers to co-create her CT-STEM data science pop-up unit. During the unit creation process, Ms. Houston explored available and published datasets online. She used a dataset from Kaggle titled "Top Spotify Songs from 2010-2019- By Year" (Henrique, 2020). The original dataset included 603 individual data points and 13 variables. Since the dataset was to be used by fifth-grade students, Ms. Houston cleaned the dataset to include only five songs from each year, for a total of 50 data points. Furthermore, she

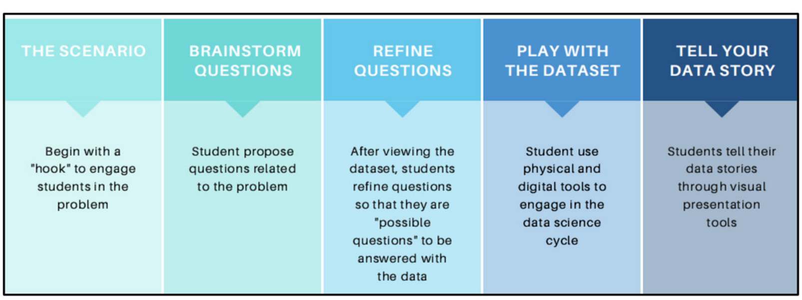

Figure 2. Data science framework designed by the researchers of this study to guide curriculum development.

reduced the variables from 13 to 8: title, artist, genre, year, BPM, duration, energy, and danceability. The energy and danceability data were included in the original dataset and were described as "the higher the value, the easier to dance to the song" and "the higher the value, the more energetic the song." After discussing with researchers, Ms. Houston left the energy and danceability data points in the set to discuss the difference between subjective and objective measures with students. Ms. Houston addressed energy and danceability data points with students by asking questions such as "Do you think it's easy to measure danceability and energy levels?" "Do you agree with the danceability and energy levels?" and "Do you think these data points are based on facts or opinions?"

After identifying the goals of the pop-up unit, Ms. Houston's goals for her students, and the requirements set by the state's general music standards, Ms. Houston and the researchers co-developed learning objectives to guide students through the unit. Although the learning objectives were created specifically for the unit, they included key elements and ideas that were already planned to be covered during the school year and met the same instructional goals for the class. See Appendix A for the complete list of learning objectives.

Throughout the unit, Ms. Houston utilized scaffolding strategies such as modeling, identifying discrete steps for tasks, and collaborative learning. For most lessons, Ms. Houston began by identifying the daily learning objective and presenting a corresponding mini-lesson. Following the mini-lesson, students worked with their groups to apply the skill or concept to their project. For example, day 3 of the unit included the learning objective, "I can identify categorical and numerical variables and identify the purpose and limitations of a dataset." For this lesson, Ms. Houston began by defining and explaining categorical and numerical variables. She then guided students through a whole-class activity to practice identifying categorical and numerical variables. Following an "I do, we do, you do" model, students then worked with their groups to categorize variables. Another example of this scaffolded support was on day 5 of the unit. The learning objective was "I can make a data visualization (or chart) using numerical and categorical variables." Following the same "I do, we do, you do" model, Ms. Houston modeled creating a chart using numerical and categorical variables. Students then collaborated as a whole group to create a chart and finally created one independently with their small groups. Students in their teams completed the data story creation and final presentation independently. Ms. Houston provided guidance and support to students as needed, such as assisting with TUVA, taking a screenshot on their Chromebooks, or answering specific questions about their project.

Data collection, analysis, and validation

We used a narrative case study as our research design and the product of our inquiry (Connelly & Clandinin, 1990; Creswell, 2007). We explored a single case over one year through "detailed, in-depth data collection" (Creswell, 2007, p. 78). Our case is bound by one teacher implementing and refining a data science unit and her associated classroom practices. We chose Ms. Houston as our case because it was "intrinsically interesting" (Merriam, 2009, p. 42) and would uncover useful mechanisms behind the effective integration of data science and non-STEM subjects in elementary classrooms. We deemed the case intrinsically interesting as Ms. Houston was a music teacher drawing on a topic aligned with popular culture while integrating data science and mathematics instruction. This instruction was novel to her everyday teaching practices. Furthermore, related arts teachers (i.e., specialists in art, music, or physical education) typically have less scheduling flexibility than general education teachers making it challenging to offer innovative instruction that might include technologies, methods, or collaborative tasks that require longer blocks of time. We move through the narrative case study chronologically providing a description and analysis for each implementation day.

Our data sources included: (1) in-person observations during implementations, which noted choices and challenges encountered during implementations; we observed how the teacher used data practices and integrated interest-based, student-centered, and relevant activities; (2) video observations using a Swivl (https://www.swivl.com/) recording device to capture the teacher's movement and language while teaching; (3) reflective teacher journals with prompts completed once a week during the implementation process; (4) two post-interviews to discuss the teacher's experience with data science instruction and ways it informed her implementation practices, including benefits and challenges of implementing the unit; and (5) artifacts including her data science unit, photos to assist in documenting the process, and students final data stories. See Appendix B for additional details regarding each data source.

We used an *inductive* approach to video analysis (Derry et al., 2010) in which researchers watched all available video recordings, reviewed artifacts, and read all transcripts and observational notes. During the narrative analysis, two research team members first reviewed each data source. They summarized the substance of the narrative by identifying broad events and the sequence in which they occurred, relying on the data science framework (Figure 2) and the teachers' daily instruction documented across data sources to assist in constructing the narrative (Merriam, 2009). Next, one researcher wrote the narrative in greater detail using the data sources to determine the meaning of the teacher's actions and then met with the second researcher to discuss the interpretation and reach consensus regarding the story's accuracy. Finally, we met with Ms. Houston to co-construct and negotiate meaning (Clandinin, 2006) by engaging in member checking and dialogic approaches (Harvey, 2015) to augment her voice in the narrative analysis and increase the validity of our findings. Ms. Houston is also an author of this article and chose her pseudonym to honor the late singer Whitney Houston.

To attend to the validity of this study, we relied on Yin's criteria (2017) for judging the quality of case study research design. The inclusion of Ms. Houston in the data analysis and writing and our multiple data sources contributed to the *construct validity* of our study. Our systematic interpretive reflexivity practices among two researchers, technique of pattern matching, and intentional time-series analysis contributed to *internal validity*. Our single-case study's grounding in socio-constructivist learning theory, repertoires of practice, and the data science framework contributed to *external validity*.

Findings

We draw from all five data sources to describe Ms. Houston's teaching practices in the context of our data science curricular framework. We focus on adapting the data science framework, integrating data science practices with music content, and integrating children's everyday discourse with domain-specific discourse.

Scenario and driving question: Description (day 1)

On the first day, Ms. Houston introduced the CT-STEM data science pop-up unit to her class. She used a template slide format that she typically used for her lessons, which included a "Question of the day," "Rhythm of the day," and the learning objective in first-person language (Figure 3). Ms. Houston guided students through clapping the rhythm of the day and then moved on to another daily practice, briefly celebrating a musician's birthday and providing history about the musician.

After engaging in her daily practices, Ms. Houston displayed the title of the pop-up unit, "Bop or Flop? Using data science to design a popular song." Then, she introduced the next activity by stating she would play popular songs from Billboard charts top 100 songs of 2021, and students

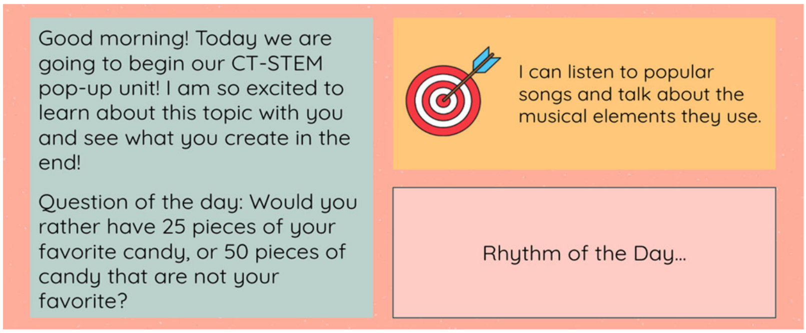

Figure 3. Ms. Houston's display at the front of the class on day one of the pop-up.

Table 1. Students' responses to two questions about mechanisms driving song popularity.

Question	Response Category	Student Examples
What makes a song popular?	Social media	"Because of TikTok people get famous"
	Artist characteristics such as dedication, talent, and previous body of work	"When the artist believes it is good" "The artist's talent" "What they done in the past"
What musical elements are important when trying to write a song?	Components of a song including pitch, melody, tempo, and lyrics.	"The steady beat makes it" "The pitch and tempo" "Tone and melody"
	Genre	"They are all pop and hiphop"

would raise their hands if they had heard the song and then guess the song title and artist. The first song she played was Driver's License by Olivia Roderigo. As Ms. Houston played the music, several students sang the lyrics and swayed to the music as they sat on their carpet squares. While playing short clips of the songs, students vocalized their observations, and Ms. Houston encouraged this practice. For example, one student noticed that "There is no country music on the list," and another noted "This [a song by Adele] is a sad song."

After this sensory activity, Ms. Houston organized students into small groups in corners of the classrooms, asking them to discuss the songs and answer the following questions: What makes a song popular? And What musical elements are important when trying to write a popular song? After discussing in groups, students individually wrote answers to the questions and placed them on the large posters. Students' responses fell into four categories: social media, artist characteristics, genre, and musical components of a song (Table 1). In her reflection journal, Ms. Houston noted that children enjoyed the activity and connected the content to their lives in meaningful ways. She stated, "I think since the content of the unit (music they listen to) is so relatable, they are really connecting with the data and making meaningful connections with their learning." She also indicated that many students were "passionate" about popular music, which allowed for engagement with data science practices. She wrote, "I believe popular music is a topic students are passionate about. It is easy for them to 'argue' and discuss if they agree or disagree with the data and what is popular. In my opinion, these conversations have helped deepen understanding of the data and what it is showing us."

After students generated mechanisms that drive popular music, Ms. Houston reorganized the students into their individual positions on their carpet squares. She restated the questions and displayed the scenario to the class. While reading the scenario, she emphasized that students would be role-playing as music producers and their goal was to produce a popular song to make money. She explained that students would explore data and make a pitch to a musician on how to create a successful song together. She defined a pitch as "requesting someone to work with you."

Scenario and driving question: analysis

On the first day of the pop-up unit, Ms. Houston continued her daily introductory teaching practices. She did not abandon her typical practices, which in turn, helped integrate the pop-up unit into the existing culture and climate of the classroom. Before presenting the pop-up scenario or dataset, Ms. Houston chose to engage students in an immersive song-listening activity to appeal to students' everyday experiences and emotions. She encouraged children to sing, dance, and discuss the music, thus bringing in enjoyable everyday music listening practices to the classroom. In the following activity, she asked students to answer the questions, "What makes a song popular?" and "What musical elements are important when trying to write a popular song?" on sticky notes and displayed them in front of the class. The first question was the driving question in this data science pop-up scenario. The second question purposefully focused students on music content knowledge, guiding them to generate possible music element variables driving the success of popular music. In this activity, students took an analytical lens to their everyday experiences with popular music and externalized their analysis by answering the specific questions that she posed. Relying on learners' natural curiosities and inquiry-driven natures, Ms. Houston integrated everyday understandings (popular music), music domain content (musical elements of songs), and initial data practices (hypothesizing and generating data).

Playing with the dataset: description (day 2 - 6)

On the second day, Ms. Houston placed students into their "production teams" of 3 - 4 members. She displayed and read the driving question in front of the class. Then, she displayed photos of student sticky note responses to the questions from the previous week. After reviewing the responses, she transitioned to the dataset for the unit explaining that students would use the data to answer the question. After asking students their definitions of data, she defined data as "facts/statistics collected on a topic and used for reference or analysis." She asked students "what kinds of data points do you think will be available about music?" Student responses included, "genre," "tempo," and "how many albums sold."

Ms. Houston gave each student a paper copy of the dataset in the format of a spreadsheet (Table 2). Each row represented a song, and each column represented a characteristic of the song. The dataset contained the top 5 songs on Spotify for each year from 2010–2019 which resulted in 50 song titles and 7 corresponding variables: artist, genre, year, beats per minute (BPM), duration in seconds, energy score, and danceability score. Ms. Houston noted in her journal entries that she downloaded and modified the Spotify data from Kaggle: "I made my dataset smaller so that students were only working with 50 songs (5 from each year) instead of nearly 700 songs." Students reviewed the dataset in their production teams. Then, Ms. Houston asked students to stop their discussions. She defined and reviewed the meaning of the variables. Finally, she asked students, "Do you think this data will tell us *why* these songs are popular?" and asked them to discuss in their groups. When they came back together, Ms. Houston called on one student, Alyssa, who noticed "beats per minute is pretty high on all of them." Ms. Houston exclaimed to the student, "Kiss your brain! Does it say that because the BPM is high, this song is

Table 2. The first five rows of the dataset Ms. Houston gave to students. Students' dataset contained the top 5 songs from 2010 through 2019, which totaled 50 songs.

	Title	Artist	Genre	Year	BPM	Duration (secs)	Energy	Dance
1	Hey, Soul Sister	Train	pop	2010	97	217	89	67
2	Tik Tok	Kesha	pop	2010	120	200	84	76
3	Bad Romance	Lady Gaga	pop	2010	119	295	92	70
4	Just the Way You Are	Bruno Mars	pop	2010	109	221	84	64
5	Baby	Justin Bieber	pop	2010	65	214	86	73

popular? Does it say that?" Alyssa replied, "No." Ms. Houston responded directly to Alyssa, "But do you notice something in the data?" Ms. Houston turned to address the class, "Alyssa notices that the tempo is all high on all of them, so it might not say that word-for-word, but she notices a trend." Here, Ms. Houston highlighted a data practice of how spreadsheet data can be interpreted. She explained that the data does not explicitly explain *why* songs are popular, but the reader of the data can "notice trends" by observing patterns within and among the variables.

On the third day of the unit, Ms. Houston continued with her daily practices, including celebrating a musician's birthday. The date was October 31st and the class celebrated Robert Van Winkle's birthday, who is more commonly known as Vanilla Ice. Connecting her daily practice with the topic of the pop-up, Ms. Houston exclaimed, "He is what we call, ladies and gentlemen, a one-hit-wonder, which means he had one song that was really popular; he was super famous. And then he released other songs, and they were never quite as good or as popular." Here, Ms. Houston noted the varied success of songs from one artist. After engaging in her typical daily practices, Ms. Houston explained that students were going to view a dataset and generate questions that could be answered using the dataset. The learning objective for this day was displayed as "I can identify categorical and numerical variables and identify the purpose and limitation of a dataset." Then, she displayed the words "categorical" and "numerical" and asked students to "guess what these words mean." Some students raised their hands and offered their guesses. After a few responses, Ms. Houston displayed the definitions as 1) Numeric: Measure numbers/quantity and answer the question "how many?" or "how much?" and 2) Categorical: Names, labels, or observations that can be categorized and sorted into groups. Then, she turned the students' attention to their dataset. She asked students to determine which variables were categorical and numeric in the dataset. While students discussed in pairs, Ms. Houston walked around to groups asking probing questions such as, "Why do you think it is called categorical?" One student replied, "It sounds like category," while her partner provided an example of a category stating, "Take everything that's, like, green." When Ms. Houston brought the class back together, she asked for examples of categorical variables. Two students responded with "genre" and "artist." When she asked for examples of numeric variables, two students responded with "duration" and "year." Ms. Houston paused to explain that although "year" consisted of numbers, it was considered categorical. She pointed at the definitions and stated, "the songs are not based on *how many* years but *what* year they came out." After the discussion of the dataset, Ms. Houston engaged the class in a variable sorting exercise. With student input, Ms. Houston dragged and dropped items such as weight, hair color, age, and dog breed under the heading of "numeric" or "categorical." Then, the class repeated the activity with all the variables from their dataset.

On the fourth day, Ms. Houston again engaged students in their daily practices and identified the learning objective as "I can make a data visualization (or chart) using numerical and categorical variables." She displayed the driving question for the pop-up and directed students back to their datasets. Ms. Houston explained that the class would plot data from two variables on a large poster in front of the classroom. As a class, they decided to choose the numeric variable, BPM, to plot against the year. Ms. Houston assigned each group to choose one song from an assigned year and identify the BPM for that song. After a few minutes, she asked each group to vocalize their chosen song and BPM value, and she drew a bar graph corresponding to that value.

After this class activity, Ms. Houston asked students to reconvene in their teams, choose a categorical and numeric variable from their datasets, create a graph using markers and posters, and present their work. She provided directions and templates for communicating findings from their data visualizations (Figure 4). For example, one group plotted artist versus energy (Figure 5).

Ms. Houston engaged the group in a question-and-response interaction in front of the class (Figure 6). She asked about minimum and maximum energy values on the chart. Then, she asked if the team agreed that the song with lowest energy value, "All of Me" by John Legend, was

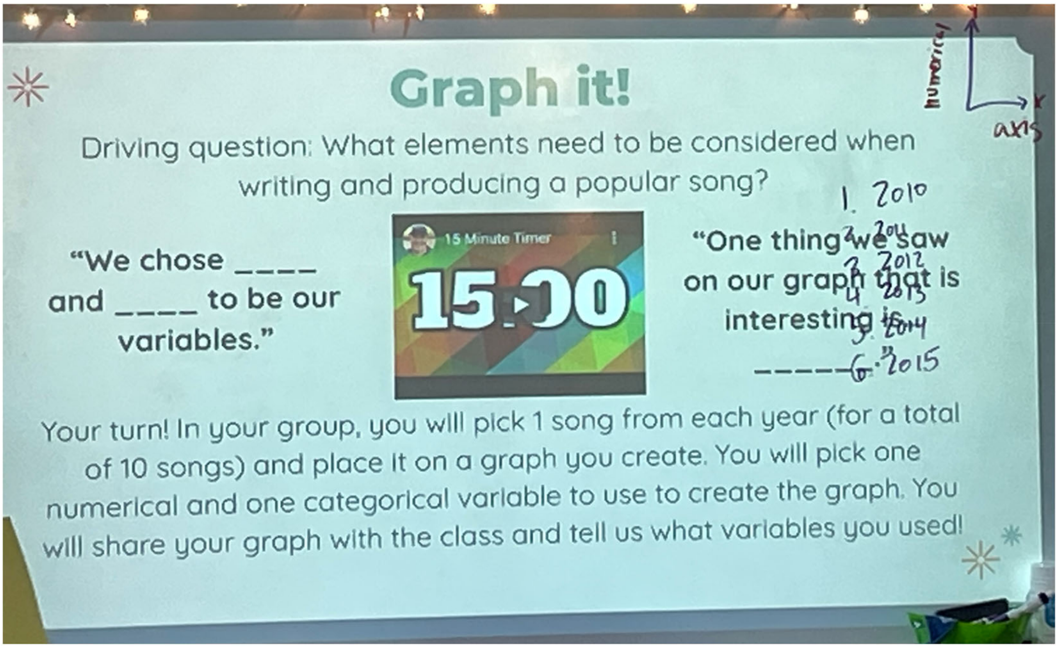

Figure 4. Ms. Houston's slide displayed in front of the class with directions and communication templates.

indeed a "low energy" song? One student immediately disagreed because she "loves that song." Ms. Houston then clarified that a song can have low energy but still be enjoyable.

On the sixth day, Ms. Houston engaged in her daily introductory practices and then explained that students would explore the digital graphing tool, TUVA, in their teams. The learning objective for this day was "I can explore data and decide what visualizations will help me tell a data story." She walked through features of the tool such as clicking on a data point to view more information and how to change from a dot plot to a bar graph. After the group demonstration of data visualization practices using TUVA, Ms. Houston asked students to access TUVA and the preloaded dataset on their individual computers. She once again displayed and reviewed the driving question while students investigated the dataset.

Playing with the dataset: analysis

To connect students' everyday understandings with data science content and practices, Ms. Houston leveraged student use of language. For example, when Ms. Houston introduced the concept of categorical and numeric variables, she identified a cognitive conflict between children's everyday definitions that categorical variables are categories and numeric variables are numbers and the variable "year" in the dataset. Although "year" consisted of numbers, Ms. Houston considered it a categorical variable. When explaining this discrepancy, Ms. Houston emphasized "how many years" constitutes a numeric variable and "what year" constitutes a categorical variable. When Ms. Houston assessed student learning, she discovered that students still considered year as a numeric variable. In turn, she further explained the categorical nature of "year" when she emphasized that students were "looking at a set of years" and wrote each year on the board. Here, Ms. Houston continued using everyday language to further clarify understanding rather than using the mathematics language of continuous and discrete values.

In another example, Ms. Houston noticed everyday language contributing to misconceptions and addressed this issue. When she engaged in a discussion with the team who presented a plot

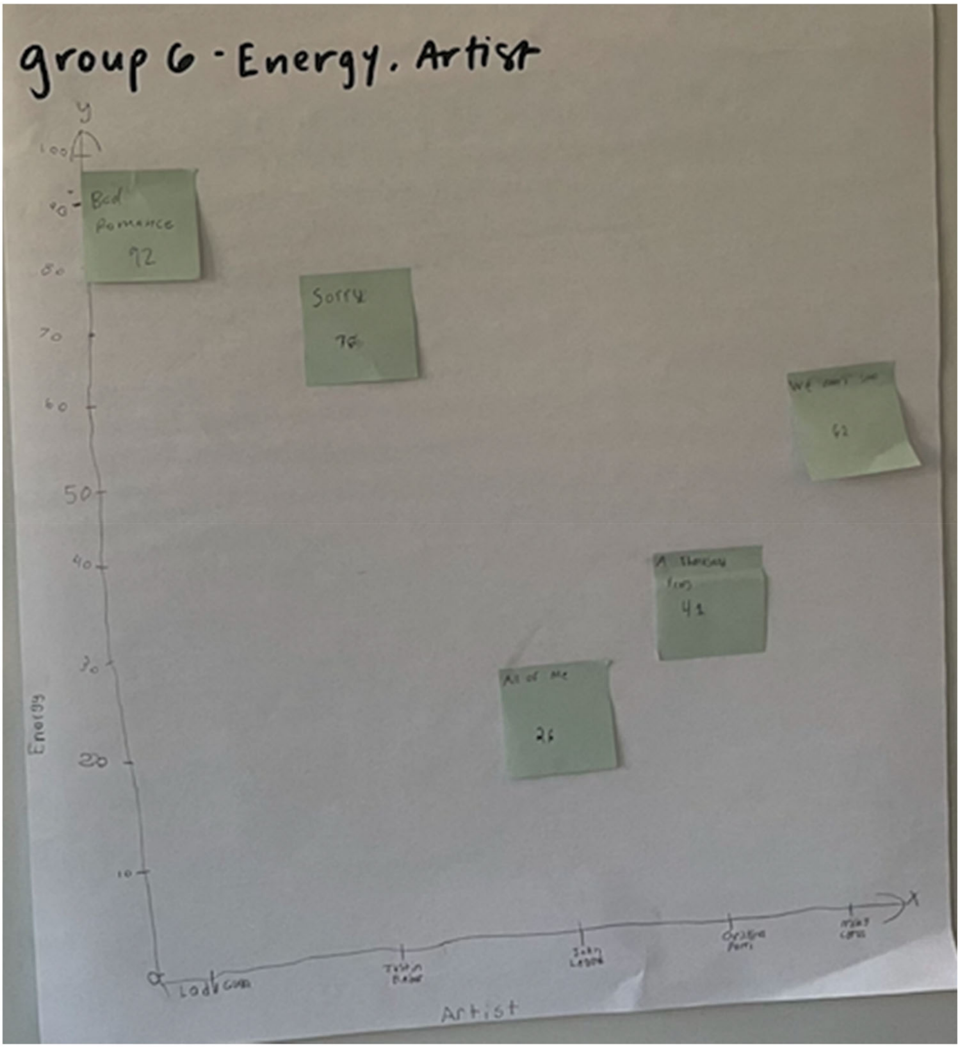

Figure 5. Example of one group's plot of artist versus energy score.

of artist versus energy, she asked if students agreed that "All of you" by John Legend had low energy. One student immediately disagreed. When Ms. Houston probed further, the student responded, "Because. I love that song!" Then, the student quickly changed her mind and stated, "Actually yes." Although the student self-corrected, Ms. Houston reiterated to all students that they can enjoy songs with low tempo or energy. Here, Ms. Houston is once again disentangling students' everyday discourse with domain specific language. The student immediately interpreted "*low* energy" as pejorative and therefore, defended the song she loved from being labeled as low energy. However, Ms. Houston clarified that a song could simultaneously be desired and have low energy or low tempo.

Ms. Houston also made choices in terms of integrating statistical content knowledge and data practices to support students' everyday understandings. She assigned each group a year to investigate in the dataset. Each group identified one song from that year and the corresponding BPM. Then, the class constructed a bar graph based on those values. Here, Ms. Houston guided students toward identifying a *typical value*, which in mathematics is a method for identifying a single value that is representative of a set of numbers. In mathematics classes, teachers often obtain

Ms. Houston:	Which one is your numerical?
Student 1:	Energy
Ms. Houston:	Energy! What was the song with the highest energy level?
Student 1:	92
Ms. Houston:	And what song was that?
Student 1:	Bad Romance
Ms. Houston:	And what was the artist?
Student 1:	Lady Gaga
Ms. Houston:	Very nice. What was the lowest one?
Student 2:	22
Ms. Houston:	What song was that? And the artist?
Student 2:	All of me. John Legend.
Ms. Houston:	Do you agree with that? Based on–you've heard these songs–right? Do you agree that one has kind of low energy?
Student 2:	No.
Ms. Houston:	Why?
Student 2:	Because. I love that song! Actually yes.
Ms. Houston:	Well, can it have low energy but still be a song you really like?
Student 2:	Yeah.
Ms. Houston:	Can it have a low bpm and be a song you really like?
Student 1 and 2:	Yeah.

Figure 6. Ms. Houston's answer and question session with one team regarding their graphic in front of the class.

a typical value from a set of numbers by calculating the mean or median. In contrast, in this music classroom, the teacher obtained the typical value by asking students to choose one data point as a proxy for that value. By adopting a non-mathematical approach of students arbitrarily choosing a value, Ms. Houston avoided the potential difficulties of (re)teaching students how to calculate a mean, a relatively new skill for fifth grade students. This way, Ms. Houston included all students in the data science practices regardless of their mathematical abilities. While Ms. Houston chose an inclusive approach, arbitrarily choosing a value to plot is likely to result in less accurate interpretations of the data compared to mathematically calculating a typical value and may lead to student misconceptions in the future.

Creating and telling a digital data story: description (day 7 – 9)

On the seventh day, Ms. Houston engaged students in the daily introductory practices and displayed the learning objective: "I can create and use data visualizations to tell a data story." Then, she presented an example pitch presentation which began with slides that directly answered the driving question with a claim: "The most important elements when producing a popular song are genre and BPM" and a corresponding suggestion: "For our popular song, we would write a pop song that has a BPM of 120 or higher." The remainder of the presentation provided evidence for the claim and suggestion using digital data visualizations created in TUVA. Students worked on their presentations for the remainder of this and the following class session.

On the ninth day, Ms. Houston engaged in the daily introductory practices and then enthusiastically announced that students would give their pitches today. All five student teams presented their pitches, and every student in each group played a role in the presentation. Each team used the template provided to present two visualizations (except for group 1, who presented four graphs), made at least three data-based claims, and provided a final suggestion for developing a popular song that could rank highly on music charts. The argument logic was similar across all groups. Three teams began their pitches with claims alongside data visualizations and then concluded with a suggestion. In contrast, two teams began with one or two claims, displayed their data visualizations after presenting them, and concluded with a suggestion. For example, one team introduced their pitch with the following statement displayed on a slide: "We think the most important elements of making a song is BPM and duration." Then, they defined the terms BPM and duration and displayed two claims about those variables in the dataset: "The average duration is 2 min and 50 s" and "The average BPM for a song is 100 - 120." They also displayed their data visualizations along these claims. Based on these claims, the final slide displayed a final suggestion: "It should have a BPM between 100 - 120 and a duration of about 200 s (2 min and 50 s). It should also be a pop song because that is what is popular" (Figure 7).

All teams' data visualizations contained plots with two numeric variables or one categorical and one numeric variable. Four out of the five teams displayed two bar graphs, and one team displayed two bar graphs and two dot plots. All students made appropriate choices regarding the type of graphs for displaying the information. However, students made different choices in terms of selecting a third grouping variable (Figure 8). Out of the twelve graphs displayed, two graphs did not have a grouping variable, six graphs had a grouping variable that was the same as one of the two axes variables, and four graphs had a third group variable that was not the same as the two axes variables.

In addition, all teams made claims about a typical value on each data visualization. For example, one team noted, "The average BPM (tempo) is about 110 and 120," and another team

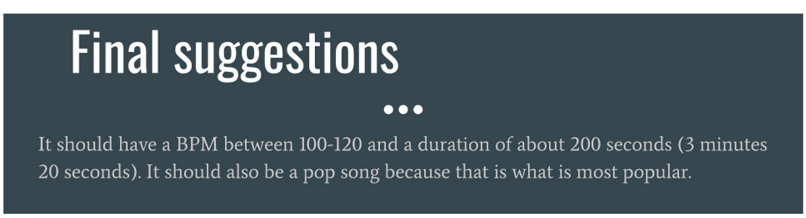

Figure 7. One team's final suggestion slide.

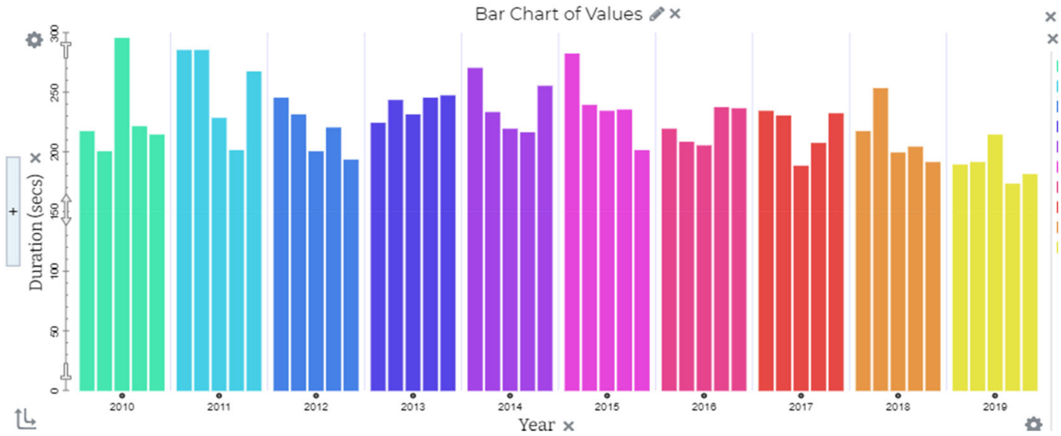

Figure 8. Example of one student teams' data visualization illustrating Duration versus Year with Year as the grouping variable. A bar graph with one grouping variable that was the same as the categorical or numeric variable was the most common choice among student teams.

noted, "The average energy level is about 70." All students chose the term "average" to describe their typical values. However, no students calculated mean values. Instead, all teams estimated the average and verbalized their estimations using words such as "about" or offering a range of values.

Creating and telling a digital data story: analysis

In their pitch presentations, student teams visibly demonstrated their abilities to make an argument based on a dataset and to integrate their knowledge about music elements with data science practices. During their presentations, Ms. Houston asked students to deepen their explanations and discuss their thinking further. The presentations showed how Ms. Houston consistently made student learning and discourse visible throughout the pop-up unit. After students presented their work, Ms. Houston concluded, "I can tell students understand the data, their data story, and the visualizations they are using."

Ms. Houston also described how students engaged in music content and discourse practices: "From a musical side … [students] were really able to see in real life context what it's like to analyze music and talk about music–why you like it or why you don't like it and see all the elements that are involved in music production." At the same time, the music content exploration was driven by data science practices. Ms. Houston noted, "From a data science point of view, I think it was really cool to see them combine their opinions on what they like versus what the data says is popular." She noticed that students learned to separate their opinions from the trends in the dataset, particularly if they did not agree with conclusions drawn from the data. For example, in her interview, Ms. Houston stated that although most songs had relatively high bpm, some students did not enjoy "songs that are fast." She noted, "But then [students] could see 'well, in this dataset, like the most popular songs are the ones that are fast. So even though I don't like it, in general, that's what it is.'"

However, Ms. Houston noted some challenges with students talking "about the why" when making a data-based argument. Students argued for trends they noticed in the data but did not put those trends together to tell a coherent story. She felt that telling a coherent story may have been challenging for students because "there wasn't one right or wrong answer … Just because I say tempo and you say genre doesn't mean either one of us is wrong. I think [not having one right answer] was difficult for them. But I think that it helped them. I think it pushed them." In other words, Ms. Houston introduced students to inquiry-driven problem-solving with multiple solutions and claims supported by the data. She noticed that this form of ambiguous solution-seeking may have been challenging for students. She continued,

> "I would say that [the analysis] is maybe the trickiest part for my students and me because the way that the variables being very, like, **not one clear answer, like, one perfect—this is why the song is popular… Just because it was a high tempo or something doesn't necessarily mean that that's why it was popular.** Is that a trend you notice over the songs? Like does that mean that's why it's popular? Or is it just like, you know… But it kind of lent itself to letting them pick and choose and it still being right, or they could still make an argument for it."

Here, Ms. Houston transitioned into another related idea: that not only was it novel for students to solve problems with multiple, acceptable solutions, but more specifically, that it was challenging to pinpoint *why* these songs were highly ranked, even when basing their reasoning on evidence from a dataset. In other words, the dataset still needed to provide an absolute explanation; there was still some uncertainty as to why these particular songs were popular. In actuality, there is always uncertainty working with any dataset as data are just abstractions of the world. However, in this case, additional steps could have been taken for students to develop more coherent data stories. For example, students needed access to a comparison dataset of non-popular songs, which they could have used to test their claims about popularity mechanisms. Moreover, additional variables could have provided more information about the popularity of the songs dataset, such as social media presence, artist characteristics, and lyrical analysis. Thus, in her reflections, Ms. Houston was uncovering uneasiness regarding how she and her students could not go "an extra level to talk about the why " and make causal inferences based on the limited dataset. Although Ms. Houston stated that working through ambiguity and uncertainty with real-world datasets was challenging for students, she noted that they were able to "pick and choose" and "still make an argument" for the claims they presented.

In addition, students needed help with knowledge around typical values. Ms. Houston did not include the calculation of typical mathematical values, such as mean or median, in the pop-up unit. As described earlier, Ms. Houston asked students to obtain a typical value by selecting one data point as a proxy for a typical value. This choice resulted in bypassing potential impediments with children who may not have had the requisite mathematics skills and in turn, provided equitable access for all students to engage in data sciences practices. Although her approach provided accessibility and engagement for all students, there were misconceptions that appeared in the final presentations regarding the term "average." For example, one team claimed that "the average duration is *about* 200 s," and another team claimed, "the average bpm is 100 - 120." However, calculating the average of a series of numbers results in one precise number, not a range or estimation. In her post-implementation reflections, Ms. Houston noticed this misconception and stated, "I don't use this [mathematical] vocabulary every day… so, maybe I could have been more accurate with some of those other things." At the same time, Ms. Houston defended her pedagogical choices to engage and expose her students to data science practices in ways that were meaningful to her students: "I am happy with the result though. Even with things that were missed or 'off,' I think overall, they were able to decide what things were important and make a graph to support it… They can now see more flexibility in data science and use data science in a different way."

Implications

The findings and analyses in this study suggest that in order to implement a CT-STEM data science pop-up unit in her elementary music classroom, Ms. Houston continued her daily routine teaching practices, integrated music content with data science practices, and integrated students' everyday discourse and experiences with music and data science. Her reflections and our analyses demonstrate successes in students' abilities to become excited about the topic, generate opinions based on their everyday experiences, and integrate their everyday discourse with data science discourse. The class integrated music content knowledge with data science practices by creating data visualizations to support claims about musical elements of popular songs. Our primary claim in this article is that by connecting 1) everyday discourse, 2) domain content knowledge, and 3) data science practices, teachers can effectively integrate data science education into the elementary classroom and particularly for non-STEM subjects. Our hypothesized framework (Figure 9) displays the domain content, which in this study was music, at the top of the figure because the domain content is what grounds and drives the integrations of data science practices and everyday discourse, as indicated by the findings.

Our study has several implications. First, data science education has historically been integrated into math, science, or computer science classrooms (Wilkerson et al., 2021). In our study, Ms. Houston's case provides an example of incorporating data science into an elementary school subject that typically does not include data science practices. The findings suggest that data science practices can be integrated into non-STEM classes by relying on domain-relevant datasets and having students engage in data practices driven by domain content knowledge. As a result, elementary school students can learn data science practices related to creating visualizations and telling data stories. Such practices include making domain-relevant claims based on data, creating visual explanations to support claims, and providing a narrative structure to the explanations (Davenport, 2013). Moreover, our findings also support that data storytelling is a way for teachers to engage and expose children early to data science and encourage personal connections with the data (Kahn, 2020; Kahn & Jiang, 2021; Wilkerson & Laina, 2018). Our analyses and reflections also led to discussions on deepening students' data science practices and knowledge for future iterations. For example, we anticipate that providing students with datasets that support comparative analyses can lead to making stronger and more valid claims. In this unit, the lowest ranking five songs could be added to compare high- and low-ranking songs. In addition, students could explore the limitations of their analyses by suggesting confounding variables and imagining how additional data may change their claims. These adjustments to the unit could address earlier comments from Ms. Houston about her uneasiness with students not being able to go "an extra level to talk about the why" in their data stories.

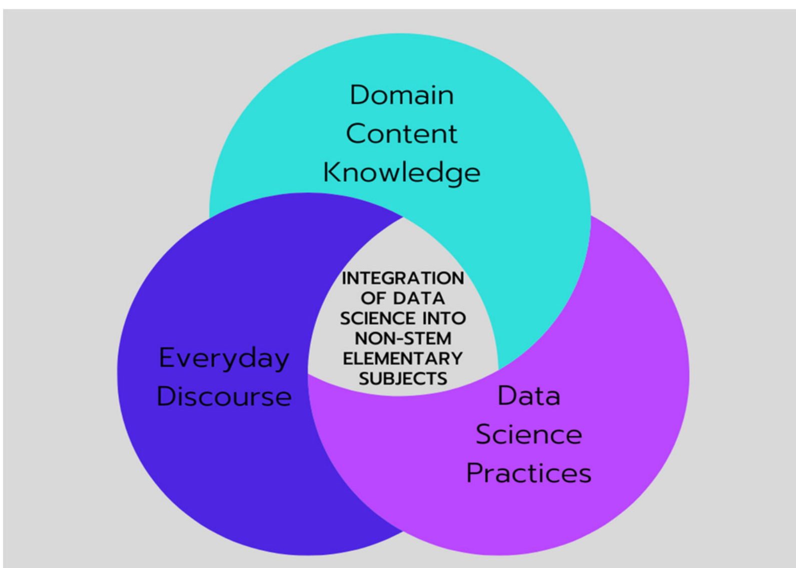

Figure 9. Our hypothesized three-part framework indicating the inclusion of domain content knowledge, data science practices, and everyday discourse for integration of data science and storytelling into non-stem elementary subjects.

Second, this case is an example of how a teacher's connection to children's interests and natural discourse shaped their data practices. The teacher implemented data science in a non-STEM classroom to expose children to data science in other domains that are of interest to children. Beyond connecting to their everyday interests, when teachers notice and build on children's everyday language discourse, it can lead to student engagement and learning of the content and practices (Kahn, 2020; Rosebery et al., 2010). This requires teachers providing space for students to express their epistemologies, to notice when cognitive conflicts occur between every day and domain-specific language, and to address such conflicts by merging everyday and domain-specific discourse (Gutiérrez et al., 2009). However, teachers will face developing tensions and *need to consider tradeoffs* when merging everyday discourse and data science practices (Figure 9). On the one hand, teachers could fully ground the teaching and learning in everyday discourse, which engages students, but this approach may lead to misconceptions or inaccurate conclusions, as we saw in our findings. Alternatively, teachers could avoid everyday discourse and focus on domain-specific language and practices, which is more accurate from the domain point of view, but this approach may alienate children and reduce engagement. In our study, we conducted an *inductive* analysis that led to discovering this tension between the every day and data science practices. To more deliberately investigate this tension and our hypothesized framework shown above in Figure 9, we suggest that researchers adopt our framework *deductively* and explicitly when designing their studies and during pre-implementation co-design with teachers. Practically, to support teachers more fully in navigating such tensions, in future summer RPP meetings, researchers will ask teachers to identify domain areas and language that they would like to focus on, and researchers will support this plan of study. Ms. Houston suggested that teachers could create a reference sheet during PD with relevant domain content that could be used to guide instruction.

Finally, this case is also an example of teachers and researchers co-designing curricula. In the summer RPP meetings, teachers and researchers cultivated an equitable community of practice and developed social and professional relationships with one another (Arastoopour Irgens & Herro, 2023). Similar to other co-design RPP's (Coburn et al., 2021; Klar et al., 2018), these relationships continued into the implementation of the pop-up unit where researchers were available to support teachers as they worked with their students, drawing on the expertise of both parties. In turn, a teacher-driven and researcher-supported process facilitated the integration of what is typically a non-STEM domain and data science. Moreover, the framing of the unit as a pop-up emphasized how the unit was an opportunity for teachers to interactively immerse their students in material that is not typically covered in traditional curricula and that meets their interests (Tranquillo & Matthew, 2015). In our case study, the pop-up label encouraged teachers to think unconventionally about integrating data science practices into their domains in ways that intrigued their students.

Limitations and challenges

In addition to the implications, we acknowledge several limitations with this research. First, this is a single-case study of one teacher, which limits generalizability; however, this choice purposefully reflects our in-depth exploration in a typical music classroom (Merriam, 2009). Thus, the intent of this case study is not replication but transferability to help educators make connections between similar practices and ways they might be useful in other elementary classrooms. Second, the teacher was motivated and engaged in the entire process of co-creating and implementing the data science unit and worked in a supportive environment—a STEM school. While her music classroom was typical of many elementary schools, we acknowledge that working in a STEM school may have impacted the successful creation and implementation of the unit, and other teachers may not have similar support or resources. Third, data collection procedures impact the interpretations presented in this study. Specifically, we chose to use Swivl camera technology, which focuses on the teacher and follows her around the classroom. The teacher wears a microphone and audio involving and closely surrounding the teacher is recorded. Therefore, this study did not collect video and audio that did not directly involve Ms. Houston. Video of students interacting without Ms. Houston could contribute additional or differing evidence for this study. Although classroom observational notes supplemented the video analysis and provided validity checks, such notes are also limiting in that notes are subject to each researcher's bias and ability to record notes. Lastly, according to Ms. Houston and evidence of student artifacts detailed in the findings, students developed data science practices such as identifying numeric and categorical variables, identifying the purpose and limitations of a dataset, making bar charts using numeric and categorical variables, communicating a solution to a real-world problem by using evidence from data. However, students also encountered challenges in terms of dealing with problems with more than one acceptable answer, addressing uncertainties in real-world data, understanding the limitations of making causal inferences, and choosing appropriate typical values. One potential reason for these learning challenges was that Ms. Houston did not know how much data science content, such as axis labels, creating and interpreting bar chats, and identifying typical means, had already been covered in another content area such as math or science. This could have been addressed by partnering with the math and science teachers to discuss prior knowledge students should have in those areas. Another potential reason for these learning challenges was Ms. Houston only held class once a week for 45 min. In turn, she spent time at the start of each class reviewing concepts, which limited the amount of new content that could be covered in each class period.

Conclusion

This research extends what is known about integrating data science curriculum in elementary classrooms, addressing an identified research gap toward better preparation for K-12 students to work with data (Lee et al., 2021). Our study demonstrates how teachers can rely on everyday discourse aligned with students' repertories of practice, domain content knowledge, and data science practices to integrate data science education into their daily teaching effectively. In this case, the domain content of music provided an engaging context for students to explore datasets and tell data stories. Given the importance of finding ways to prepare students at a young age in data science (Martinez & LaLonde, 2020), our findings highlight the importance of designing data science learning for students based on their everyday experiences and discourses. Importantly, our study informs evidence-based ways to create and implement data science education for STEM teacher education. This preliminary research offers a guide for educational researchers and schools to support new ways to conceptualize and implement data science instruction across disciplines. We encourage schools and universities looking to establish and sustain similar initiatives to consider the creation of RPP's to collaboratively set goals, support one another and share expertise toward increasing young students' data science literacies.

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Appendix A

Day	"I can" student objective	Objective from Unit Plan
Day 1	I can listen to popular songs and talk about the musical elements they use.	Make connections, get students invested in the scenario, brainstorm questions for guest speaker.
Day 2	I can ask and revise questions that will help me answer a research question.	Understanding what questions can be answered with data & making real-world connections.
Day 3	I can identify categorical and numerical variables and identify the purpose and limitations of a dataset.	Understanding and sorting categorical and numerical variables, explore TUVA and data visualizations.
Day 4	I can make a data visualization (or chart) using numerical and categorical variables.	Creating a data visualization on paper (whole group) and deciding what variables to graph.
Day 5	I can make a data visualization (or chart) using numerical and categorical variables.	Create an unplugged data visualization.
Day 6	I can explore data and decide what visualizations will help me tell a data story.	Explore data visualizations in TUVA and prepare data story.
Day 7	I can create data visualizations that will help me tell a data story.	Create a presentation that incorporates their own strengths/interests and includes data visualizations.
Day 8	I can create and use data visualizations to tell a data story.	Finish data story and make sure the audience will understand and engage with content.
Day 9	I can present my data story and self-reflect on my work.	Present data story and reflect/self-assess.

Overarching Unit Learning Objectives
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.

Appendix B

To assist other researchers who may want to replicate a similar data collection procedure, we provide additional details for each data source.

In-person observations

Our research team developed an observation protocol to collect data detailing the daily interaction between teachers and their students during data science unit implementations. Observations lasted between 45-60 min and were conducted four times during the unit by one or two members of the research team. The observation protocol included a brief descriptive information about the physical space and activities (i.e. procedures, purpose of the lesson, individual or collaborative groups), and narrative portions to note what happened in the lesson and how the teacher organized it related to data science learning (i.e., How did the teacher introduce the lesson? How did the teacher maintain the students' interests? What technologies and materials were used?) Lesson alignment to CT-STEM practices (collecting, creating, manipulating, analyzing and visualizing data) were noted and, if applicable, formative and summative assessment techniques were described. The observation form also included a space to list artifacts with consistent naming conventions to easily locate related videos and images.

Video observations

During each day of the unit, the teacher wore a Swivl recording device which captured the entire classroom space and recorded audio from the teacher and students she interacted with. In all, nine videos between 45-60 min were captured and automatically uploaded to Google Drive; this allowed our research team to watch each day of the nine-day unit several times during data analysis.

Reflective journal prompts

To assist in documenting the experience from the teacher's perspective, a digital reflective journal with weekly prompts was shared with and completed by the teacher. Questions that were asked varied each week but included inquiry or prompts such as: Describe the Pop-Up activities thus far in just a few sentences. Describe what the students did in the last few days in a few sentences. Have you made any changes to the curriculum (problem, tools or activities?) What do you believe is going well? What challenges are you encountering? What was it like working with the research/co-design team? Is there anything else you would like us to know?

Artifacts

Google Drive Folders were used to collect the teacher's instructional slides that she added to each week, students' data stories that were completed by each group of two-to-four students, and images of other activities (e.g. post-it note activities where students collected non-digital data and constructed graphs) or tools (apps, musical instruments) that the teacher used during the lesson. Both the teacher and research team collected and shared artifacts in this Google Drive Folder.