Iterative Design of a Socially-Relevant and Engaging Middle School Data Science Unit

David McKinney
dmckinn@wested.org
WestEd
San Francisco, CA, USA

Chloe Morton
cmorton@wested.org
WestEd
San Francisco, CA, USA

Brenda Tuohy
brenda.tuohy@ousd.org
Oakland Unified School District
Oakland, CA, USA

Sam Berg
sam.berg@ousd.org
Oakland Unified School District
Oakland, CA, USA

Audrey Karlstad
audrey.karlstad@ousd.org
Oakland Unified School District
Oakland, CA, USA

Courtney Ortega
courtney.ortega@ousd.org
Oakland Unified School District
Oakland, CA, USA

Zelda Allison
zelda.allison@ousd.org
Oakland Unified School District
Oakland, CA, USA

Griffin Munzel
griffin.munzel@ousd.org
Oakland Unified School District
Oakland, CA, USA

Max Washburn
jean.washburn@ousd.org
Oakland Unified School District
Oakland, CA, USA

Yvonne Kao
ykao@wested.org
WestEd
San Francisco, CA, USA

ABSTRACT

Data science education can help broaden participation in computer science (CS) because it provides rich, authentic contexts for students to apply their computing knowledge. Data literacy, particularly among underrepresented students, is critical to everyone in this increasingly digital world. However, the integration of data science into K-12 schools is nascent, and the pedagogical training of CS teachers in data science remains limited. Our research-practice partnership modified an existing data science unit to include two pedagogical techniques known to support minoritized students: rich classroom discourse and personally-relevant problem-solving. This paper describes the iterative design process we used to revise and pilot this new data science unit.

CCS CONCEPTS

• **Social and professional topics → K-12 education**.

KEYWORDS

data science education, computer science education, middle school, classroom discourse, curriculum design

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1 INTRODUCTION

1.1 Background

Data now drives many aspects of our daily lives, from the media we consume, to the products we purchase, to logging our daily health habits. Major media outlet and government agencies now create complex interactive data visualizations as part of their storytelling. The ability to understand and reason with data has become an essential skill for full participation in society. As a result, data science, a discipline that began as a graduate-level specialty, has wended its way earlier and earlier into schooling. Many universities now offer undergraduate data science majors and there is increasing attention on ensuring access to data science education for K-12 students [5, 7, 16]. At the high school level, the Introduction to Data Science (IDS) Project at UCLA Center X provides curriculum, professional learning, and support for high school data science [21].

At the middle school level, offerings are less robust. Some research groups have developed out-of-school camps and workshops to introduce middle school students to data science (e.g. [2, 19]). Code.org includes a data science unit in its *CS Discoveries* middle school computer science course [4], but this unit is not popular with teachers and students [6]. Middle school contains many great opportunities for introducing data science to students. In middle school math, students begin developing formal understanding of key concepts in statistics and data science: distributions, variability, associations between variables, sampling, and random processes [17]. The introduction of computing tools at this stage can help students manage and learn from larger data sets, which are often more effective at illustrating these key concepts [3]. However, there is little research and support for middle school data science instruction. This experience report describes our process for revising the data science unit in *CS Discoveries*, results from our classroom pilot, and recommendations for creating data science curricula that are appealing and relevant to all students.

1.2 Context

We are a team of educators from Oakland Unified School District (OUSD) and researchers from WestEd engaged in a multi-year research-practice partnership (RPP). Our team consists of two middle school computer science teachers, two middle school mathematics teachers, three subject matter coordinators and coaches, and three computer science and data science education researchers. The major goal of the RPP is to promote inclusive and equitable participation in computer science (CS) classrooms through data science. One of the RPP activities was to modify the Data and Society unit in Code.org's *CS Discoveries* curriculum, which serves as the introductory CS curriculum for grades 6-10 in OUSD. In making this modification, we included two pedagogical techniques known to support minoritized students: rich classroom discourse (see [12] for overview) and personally-relevant problem-solving [2, 9, 10, 14].

OUSD is a culturally and linguistically diverse urban school district which serves over 25,000 students. In the 2022-23 school year, computer science was offered at all of the district's middle schools. About 2,000 students enrolled in a CS course that year. The demographics of students who enrolled in CS reflected the demographics of the district, with Black students making up about 25% of computer science students, Latine students making up about 40%, female-identified students making up about 40%, and English learners making up about 25%.

1.3 Adapting an Existing Data Science Unit

OUSD uses Code.org's *CS Discoveries* curriculum as the middle school CS curriculum. *CS Discoveries* contains units on problem solving, website development, game design, data science, and physical computing [4].

The data science unit, called Data and Society, is the fifth unit in the curriculum. It is designed to take four weeks and covers content including ASCII and binary representations, cryptography, and cleaning and transforming data. At the start of the project, we surveyed all OUSD CS teachers about how they teach Data and Society and learned that most of them skip it because students find it boring and irrelevant [6].

With this feedback in hand, we undertook an iterative design process to modify Data and Society and create a data science unit that would meet our design goals and the needs of OUSD. Our design research was guided by three design-based research questions:

(1) To what extent are the data science activities relevant and engaging for students?
(2) To what extent do the teachers and students use the language routines during the activities? What additional support might be needed to encourage student discourse?
(3) To what extent do students demonstrate understanding of the data science content in their work?

2 FIRST REVISION

One of our design goals was to add supports for rich classroom discussion to the unit. OUSD uses the *Illustrative Mathematics* curriculum [11] in its middle schools, which incorporates Math Language Routines [23]. These language routines provide an explicit structure for teachers to support the exchange of student ideas. Without structured language routines, many students do not know how to talk to each other about academic content. Students in pairs or small groups may sit in silence or have off-task conversations. Whole-class discussion may devolve into a teacher-directed question-and-answer routine and/or be dominated by one or two assertive, talkative students, leading to inequitable class participation [1, 8, 12, 15]. We decided to adapt the Math Language Routines for the data science unit because students would already be familiar with them from math class. The other design goal was to build more personally-relevant problems into the unit. Based on feedback from student focus groups [6], we built the unit around a theme of "Using data to make school better."

Our revision of the Data and Society unit also had to contend with some practical constraints. The CS teachers on the project team felt the Data and Society was too long and our revised unit should take approximately two weeks instead of four. We chose to adapt only the lessons in the second half of the Data and Society unit to help meet this constraint; the second half of the lessons are more focused on manipulating and transforming data.

The project team created a seven-lesson sequence:

(1) **Decisions with data.** Identify data that can be used to improve a decision.
(2) **Gathering useful data.** Analyze data sets and explain how well a given data set can answer a question, considering factors such as size, source, question type, and sampling.
(3) **Using surveys to get data.** Write/select three survey questions to collect data and justify why they chose the types of questions they did, and who they're going to ask.
(4) **Cleaning data.** Clean and organize the survey results; describe the trade-offs involved when cleaning a data set.
(5) **Visualizing data.** Use computer-based tools to create visualizations of data and justify their choices.
(6) **Let's put it to work, part 1.** Identify a question that can be answered with a given set of data, clean and organize the data, and create a visualization to address the question.
(7) **Let's put it to work, part 2.** Reflect on trade-offs that were made in gathering, cleaning, and presenting the data.

Each lesson has a similar structure. The lesson starts with a Warm Up, during which students study a data visualization and discuss or write down what they notice and wonder about it. The Warm Up is followed by two or three Activities, a Lesson Synthesis, and Wrap Up. Throughout each lesson, language routines are used to promote discussion and encourage students to be inquisitive. The Lesson Synthesis and Wrap-Up sections ask students to reflect on the learning goal of the lesson, first as a class and then individually.

3 PILOT

We piloted the complete revised unit in one teacher's classroom over five weeks in Fall 2022. For each lesson, the team conducted classroom observations and collected student practical measures.

3.1 Classroom Observations

WestEd and OUSD staff observed the lessons of the new unit being taught. Observers took notes using an observation protocol designed to focus on the three design questions guiding the unit development. Following each observation, we organized and summarized the notes with respect to the guiding questions.

3.2 Student Practical Measures (SPM)

We collected student practical measures at the end of each piloted lesson. Practical measures are purposefully short surveys that are less intrusive and burdensome than traditional surveys. They ask participants to respond to questions about an experience right after they have had that experience, increasing the ecological validity of the measures.

Our SPM consisted of a short 18-item survey, including two open response questions and 16 Likert-style multiple choice questions. The open-ended questions asked students what the purpose of the lesson was and if they had any questions or comments on the lesson. The multiple choice items measured facets of students' engagement during the lesson, including behavioral (e.g., Were you participating?), cognitive (e.g., Did you try to connect what you were learning to things you have learned before?), affective (e.g., Did you enjoy it?), and social engagement (e.g., Did you share your thinking with other students?); and their perceptions of the lesson, including perceived challenge of the lesson (e..g, How challenging was it?), and their utility value (Can it be useful outside of school?) and importance value (Was it important?) for the lesson. The items asked students to think about what they did in class that day and respond to each item with one of four answer choices: 0 = Not at all; 1 = A little; 2 = Somewhat; and 3 = Very true.

3.3 Data Collection

The pilot teacher taught all seven lessons to two sections of CS and taught part of the unit to a third section. All lessons were observed at least once by one educator and one researcher on the team, except for Lesson 4, Cleaning Data. Three sections completed the SPM for Lessons 1 and 2; two sections for Lessons 4, 6, and 7; and one section for Lessons 3 and 5.

3.4 Results

3.4.1 To what extent are the data science activities relevant and engaging for students? Data from the SPM surveys and classroom observations helped us understand the extent to which students were engaged during the lessons and whether they found the lessons relevant. As a team, we examined the sample means for each SPM measure for each lesson (Figure 1). We did disaggregate the means by class section, but the differences do not alter the interpretation of the results for the overall sample.

In Figure 1, the four student engagement scales (behavioral, affective, social, and cognitive) are represented with circles and dotted lines. The three lesson perception scales (lesson value, perceived learning, and perceived challenge) are represented with triangles and solid lines. Students reported moderate levels of engagement throughout the unit. Overall, students reported higher mean behavioral engagement than the other facets of engagement, indicating that students were generally engaging in the activities of the lessons, but were not as engaged emotionally, cognitively, or socially. Students also reported moderate value (i.e., relevance) for the lessons. Students' perceived challenge varied the most from lesson to lesson. Students' perceived challenge generally increased over the course of the unit. The measure of perceived learning tracks with students' engagement and perceived value for the lesson. This makes sense because students are more likely to learn from lessons that they find valuable and engaging.

Classroom observations aligned with SPM data. Most students appeared to be engaged to some degree in most lessons, but engagement was often attenuated by too many transitions and work that appeared to be too easy or too hard for students. Lessons often had segments with many students on task interspersed with segments with few students on task. Some students did not reengage after each interruption to the flow of the lesson so class-level engagement declined over the course of a lesson.

In lessons where students had more time to explore the data, like Lesson 4: Cleaning Data, students reported higher levels of engagement, perceived value for the lesson, moderate levels of challenge, and higher perceived learning. In this lesson, students are given "messy" data from a survey of people's pizza topping preferences so they can plan a class pizza party. The data included multiple spellings of the same topping, and ingredient aversions (e.g., an allergy, "no meat"). Students seemed to quickly understand the need to clean the data before they could use it to make a decision. Students worked in pairs or small groups to clean the data. They discussed and debated how to categorize the data to make it most useful. For example, one student wanted to put the "no meat" response on each of the other categories for non-meat options while their partner wanted to add one to a random non-meat category. After recategorizing the data, students graphed the new categories and then participated in a class discussion of the choices students made and how to design the survey differently to get cleaner data.

In contrast to the data cleaning lesson, students reported the lowest engagement, perceived value, and perceived learning and the highest perceived challenge for Lesson 6: Let's Put it to Work, Part I. In this lesson, students are introduced to a final project in which they will construct a question about high school students and answer it using a provided data set.

The data set for the final project was a reduced version of the PISA student questionnaire data [13]. We selected a few geographic variables, demographic variables, and variables corresponding to a few questions about student well-being. We limited the data set to US respondents. This data set included 19 variables and 4,838 cases. Most of the variables contained categorical survey data: frequency categories (i.e., "Never", "Rarely", "Sometimes", and "Always") or 4-point Likert responses (i.e., "Strongly disagree", "Disagree", "Agree", and "Strongly agree").

Students were introduced to the data with a Notice and Wonder language routine. When students initially opened the data set they were clearly excited to be using such a large data set and were interested in the subject matter of the data. Despite this initial excitement and interest, it was also clear that most students were not prepared to execute the final project in the time they had to do it. Students were both unfamiliar with the data set and many did not appear to have sufficiently developed the data science knowledge and skills to complete the project. Students were provided with

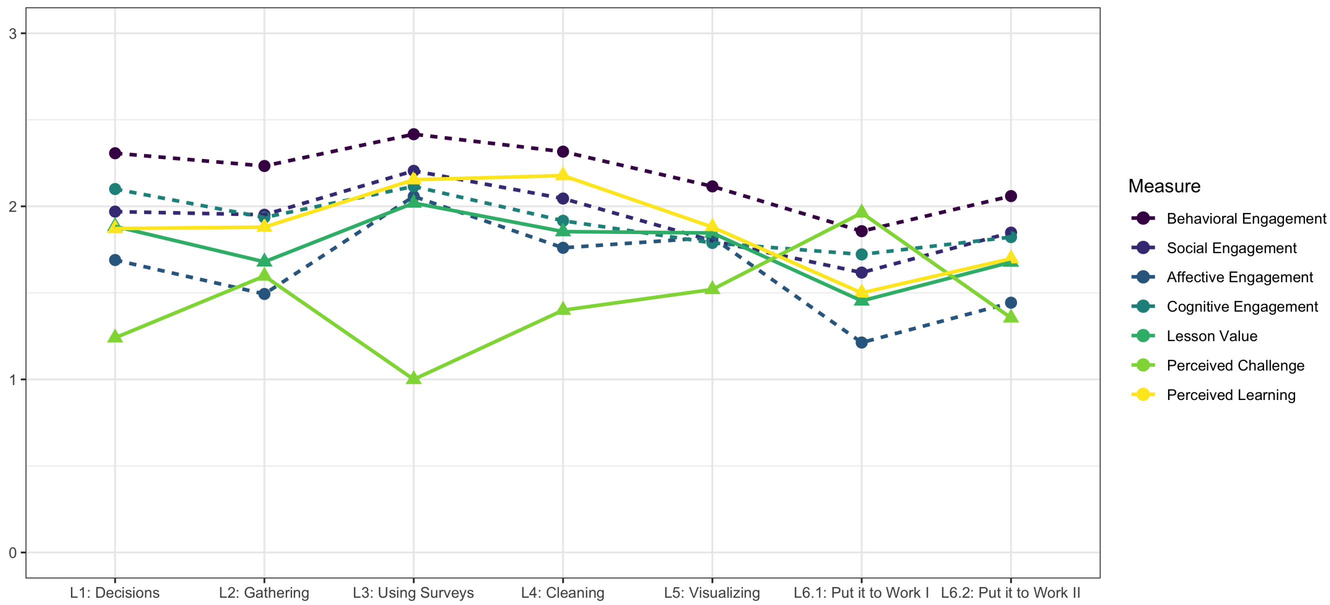

Figure 1: Sample means of student practical measures by lesson.

the data set as Google Sheet. They could choose to graph the data in Google Sheets or move it to CODAP [20]; students had worked with both platforms earlier in the unit. However, most students struggled to use either platform.

3.4.2 To what extent do the teachers and students use the language routines during the activities? What additional support might be needed to encourage student discourse? In general, the pilot teacher used language routines as planned. Students generally engaged pair or small-group discussions as directed, though they did not always closely follow the instructions for a given routine. For example, in the Stronger and Clearer routine, one student is supposed to share their response to a prompt and their partner is supposed to ask questions to help them clarify their thinking. Instead, students' conversations were more general and not as focused on making their thinking clearer.

When a language routine called for a whole class discussion, they often did not lead to a rich discussion in which students built on each others' ideas or debated a particular topic. Instead, the class often used an initiate, respond, evaluate pattern in which the teacher initiates with a question or prompt, a student answers, and then the teacher evaluates whether the answer was correct or good [22]. This is a common discourse pattern in classrooms [1], including the computer science classes taught by the pilot teacher.

While the language routines are used by math teachers in the district, the pilot computer science teacher was new to the routines and had received only a short professional development on using them. To further support the use of language routines in the data science unit, teachers likely need more professional development on how to use them effectively and lesson plans need to include more support for students to use the routines.

We also observed that lesson pacing was slow in part due to the language routines. In some cases students worked at a slower pace than expected, leaving less time to engage in the planned language routines. In many lessons, the teacher decided to skip or shorten a language routine in order to make up time. In other cases some language routines did not flow into the next part of the lesson. We concluded that fewer language routines with tighter and more explicit connection to the subsequent learning activities would improve the implementation of the language routines.

3.4.3 To what extent do students demonstrate understanding of the data science content in their work? Our classroom observations indicated large variation in student understanding of the data science learning objectives. A few students in each lesson demonstrated understanding in their written work, their work on their computers, and in class share outs. However, most students demonstrated limited understanding. For most students there were some topics that they clearly understood (e.g., that asking the 8th grade basketball team what shirt size to order would not be representative of what shirt sizes to order for the whole school) while for many other topics or tasks they did not demonstrate an understanding (e.g., how to interpret the graph they made).

The results from the perceived learning practical measure, where students reported moderate levels of perceived learning throughout, are consistent with these mixed levels of understanding. Additionally, when we looked at students' responses to the open-ended SPM question "What was the purpose of today's computer science class?" we saw that many students responses were aligned with the lesson objective while others were well off the mark.

Based on our observations, there were a number of factors that limited students' understanding. The pacing of the lessons was uneven and students generally needed more time to learn the data science. Students also needed to know some math concepts, like calculating percents, to be successful in some lessons. Some students did not have mastery of these math concepts, which slowed down their progression through the lesson and limited the time they had to develop their data science knowledge and skills.

Understanding how to use data science tools is also an important part of learning data science. Students did not have enough time using Google Sheets and CODAP to become fluent in either of them. This was likely due to the pacing issues mentioned above, but due to the unit only including seven lessons. In the lessons that used these tools, a handful of students were able to use them relatively easily while most students had difficulty.

All of these issues with students developing limited understanding of data science concepts and how to use data science tools came together in Lesson 6: Let's Put it to Work, Part I. In this lesson, students were supposed to apply most of what they were expected to have learned in the prior lessons. However, because they had limited mastery of the prior learning objectives, most students struggled on their final projects. To be successful, students had to: 1) craft a question that could be answered using the reduced PISA data set; 2) use Google Sheets and/or CODAP to clean, summarize, and graph the data; and 3) write up the answer to their question, supported by their analysis. When students had difficulty with one or more of these steps, they were less able to be successful on the others. For example, the PISA data was relatively clean, but included a few different values that represented missing data. We did not observe any student cleaning their data to deal with these different missing data values. As a result, students graphed the missing categories, which made interpreting the graph more difficult.

4 SECOND REVISION

We saw many instances of students being engaged and interested in data science and the problems we asked them to tackle. However, the inconsistent difficulty of the lessons and pacing often caused the initial engagement to dissipate. As a result, our second revision focused on improving the coherence of the unit, simplifying it, and devoting more time to key skills and concepts so that students have a clear thread to follow and can develop deeper understanding.

4.1 Improve Coherence

While we set out to create a coherent unit driven by an overarching question that leads to a final project, it was clear after the pilot that there were areas of the unit where we could improve the coherence. For example, the warm-up activities all involved different data visualizations which were disconnected from the rest of the content. We changed them all to use visualizations of the reduced PISA data set so that students would become familiar with some aspects of the data before their final project.

We also added new lessons and changed the order in order to better motivate and equip students to learn data science. The unit now starts by introducing data science and its importance. We added the lesson "Answering Questions with Data" to better prepare students for the final project by giving them opportunities to think about how choices in data visualization and analysis can help (or not help) answer different questions.

4.2 Simplify and Focus

Because students struggled to understand and develop fluency with the data science tasks, we reduced the complexity of the tasks (e.g., by providing students with a completely clean data set for the final project) and created more time within the unit for students to practice key skills. We re-sequenced the unit to introduce key skills early and allow students to practice them throughout. This included converting all the tasks to use CODAP and introducing students to data visualizations earlier and having them revisit the topic later.

We also developed a "Three Reads of Data" language routine based on our observations that students struggled to digest data sets, especially the data set in the final project. The original "Three Reads" language routine is designed to help students make sense of a math problem before attempting to solve it and inspired us to create a similar routine to support students in taking the time to understand a data set before doing anything else. In the current draft of our routine, the first data "read" is to look at the variable names and connect them to the data source (e.g., a particular survey question) and think about what data might be in that variable. The second "read" is to look at the values for each variable and understand what they mean (e.g., if survey responses are numerically encoded, which value indicates which answer choice). The third "read" is to look at the rows to understand what each case represents (e.g., an individual) and how many cases there are.

Finally, we reduced the total number of language routines throughout the unit so that there is more time for students to think and prepare for discussion as well as more time to actually hold that discussion during class.

4.3 Current Version of the Data Science Unit

The current version of the data science unit has ten lessons:

(1) **What is data science?** Explain what data science is, why it matters, and why we care.
(2) **Making sense of data.** Explain why "big data" is helpful in answering data questions; generate statistical questions based on a data set.
(3) **Visualizing data, part 1: One-variable data.** Use CODAP to create visualizations of one-variable data and use visualizations to describe the data.
(4) **Understanding survey data.** Match survey questions with the data they produce.
(5) **Cleaning data.** Create a visualization of "ungraphable" data by cleaning a data set.
(6) **Visualizing data, part 2: Two or more variables in data.** Use CODAP to create visualizations of data with two or more variables and use the visualizations to describe the data.
(7) **Answering questions with data.** Compare multiple visualizations of the same data set and analyze the effects/impacts of the different choices made.
(8) **Gathering representative samples.** Explain how well a given data set can answer a question, considering factors such as size, source, question type, and sampling.
(9) **Putting it to work, part 1: Identify and explore a data question.** Generate a "data question," select and clean data, and create a data visualization to address the question.
(10) **Putting to work, part 2: Communicating your data question.** Describe the data (shape, measures of central tendency, typical responses) as well as their process for selecting

a question, selecting and cleaning data, and the trade-offs and implications they considered.

We plan to pilot the second revision in more classrooms during Spring 2024.

5 LESSONS LEARNED & RECOMMENDATIONS

5.1 Co-Designing Data Science Lessons with Teachers and Researchers

One of the challenges we had early in the design process was building a shared understanding of what data science is and what students should learn. The researchers, OUSD coaches, and teachers all believed in the idea of bringing data science to middle schoolers, but each group brought a slightly different conception of data science and what could be realistically accomplished. Although the team met for a two-day retreat in Summer 2022 and three more times early in the Fall 2022 semester, this was not enough time to create a strong unified vision. Much of the meeting time was spent debating and discussing which data science concepts could and should be included in the data science unit, given the limited amount of time to both modify and teach the unit. Ultimately two of the OUSD coaches made most of the major design decisions for the first revision with input from the rest of the team.

The data and key takeaways collected during the unit pilot helped the team arrive at a shared understanding. The team met again for a three-day retreat in Summer 2023 to review the pilot results and plan the next major revision of the unit. By the end of this meeting, there was a much stronger sense of unity and shared vision.

We recommend that other teams who aim to do something similar devote significant time early on to exploring data science together and building that shared understanding. There are many different conceptions of "data science". The field prefers to be inclusive of these varied conceptions over gate-keeping the discipline [18]. However, this also means that it requires conscious, sustained effort to build a shared understanding of data science and how to operationalize it for instruction, especially when you bring together co-designers who have different professional backgrounds.

5.2 Data Science Lesson Design Challenges

5.2.1 Creating student data sets. Creating usable data sets for middle school students proved challenging. We wanted the data sets to be rich enough to so students could have autonomy in how they analyzed the data, to have interesting relationships between variables for students to explore, and yet be simple enough for students with limited prior experience working with data. There is little existing guidance on how to create good data sets for this age group.

The heavy reliance on categorical variables in the reduced PISA data set proved to be a poor design choice. It meant we could not leverage students' math knowledge when asking them to summarize or visualize the data. For example, we could not ask students to calculate measures of central tendency. Creating scatterplots is possible, but makes less sense with this type of data. There also turned out to be a lot of additional knowledge required for students to work effectively with categorical data. For example, students did not necessarily understand how to handle the ordinal nature of the response categories. They could create a bar chart showing the frequencies of different responses but then would order the categories alphabetically. The data set also contained several different non-response categories (i.e., "No Response", "Not Applicable", and "NA"). Initially we thought this could lead students to engage in some data cleaning or data transformation, but students did not spontaneously do so during the pilot. Students who tried to generate bar charts to show the frequency of different responses often ended with with a chart with these bars, in this order: "Agree," "Disagree," "Not Applicable," "No Response," "NA," "Strongly Agree," and "Strongly Disagree".

5.2.2 Identifying suitable tools. The team also struggled with selecting which data tools to use in the unit. Our initial plan for the unit mostly used Google Sheets, which OUSD students use in multiple subjects and grade levels. We thought there might be some advantages to using a tool that teachers would already be familiar with and building spreadsheet skills that students would still be able to use in later classes and grades. Google Sheets also enables students to create formulas, which we thought could be used to connect data science to the more programming-oriented computer science class they usually experience. However, Google Sheets has some limitations around data visualizations so we also included some instruction on CODAP [20].

Learning two different tools in the span of seven lessons was too much and students did not master either. It was difficult for students to quickly summarize and explore data in Google Sheets. Students needed support with basic spreadsheet skills, like being able to select two non-adjacent columns. Some students would resort to scrolling up and down the data sets and counting or doing other calculations by hand. Google Sheets also struggled to run smoothly on the large final data set. CODAP is a more fully-featured data analysis tool and is more intuitive for students. In future revisions, we will focus on building students' skill in CODAP.

6 CONCLUSION

In this experience report, we have described our design process for creating a data science unit that is relevant and engaging for the students in our diverse district. We look forward to implementing the current version of the unit and continuing to learn how we can better support our students and teachers in learning and teaching data science.

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