

DATA-WISDOM AS A FRAMEWORK FOR BUILDING DATA LITERACY

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ABSTRACT

In a world where “big-data” rules, the need for data literate citizens is critical. Not only do we need citizens who can read data, but also citizens who are critical of data practices that perpetuate racist practices. One potential answer for this call is to create “data-wise” citizens. The purpose of this design-based research study was to explore how secondary and post-secondary students can develop data-wisdom through the analysis of three data-inspired artistic data visualizations. This study examined the growth of data-wisdom in participants, the development of classroom norms, and the increase in positive perceptions of mathematics in participants. Data were collected through a pre-course survey, classroom audio recordings, and participant-created data visualizations. The findings suggest that teaching data science using data-wisdom practices offers an opportunity to develop this new type of citizen needed.

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CHAPTER ONE - INTRODUCTION

Data are everywhere. In the individual realm, our phones track our screen time; our watches count our steps; our web browser learns what we like and suggests more of it. Data have been used to make points about timely issues such as the spread of COVID-19 cases locally—and worldwide— and climate change; to craft critical arguments by policymakers; and inform business and marketing decisions. To reflect the growth and nature of data today, the term “big data” has been coined to refer to data that is described in terms of rapid velocity, extensive variety, and tremendous volume (Laney, 2001). As data are used increasingly in public policy debates and human-generated data become more prevalent, being able to make sense of data and understand the nature of data with a critical lens becomes increasingly important. This critical lens considers the context and ethical implications of data collection and analysis (D’Ignazio, 2017; Rosenberg & Jones, 2022). In this new era of big data, we are in need of a new type of data-literate citizen.

Given this context, it is not surprising that educational researchers have begun to encourage teachers to teach data literacy with a framework of sensemaking that leverages the exploratory nature of data analysis and inquiry about data. Such a framework includes questions that revolve around asking what we *still do not know*—rather than drawing conclusions—based on what data we have available (Taylor, et al., 2020). In such a context, mean, median, mode, and range, as well as other descriptors of datasets, become ways to note and attend to distributions and what they mean with an emphasis on context, people involved, and people impacted.

This study was inspired by a research project called The Data Visualization Project¹ (DVP). In DVP, students were asked to find a personally meaningful dataset and create an artistic data visualization that told a story based on their data. Through DVP, I saw the power data visualizations have on pushing students to build data-wisdom practices and fostering discourse in the classroom. Against this backdrop, the goal of this thesis was to utilize the iterative design process to craft an effective lesson on developing

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data-wisdom. This study follows a design-based research process (see Fig. 1) to improve upon DVP and within the study to improve methods between the two sessions of high-school and undergraduate participants.

The purpose of this thesis study is to develop a transdisciplinary curricular lesson for secondary and post-secondary students that expands upon the current work being done in the artistic data visualization space by adding the element of data-wisdom. This addresses the call of data science researchers to foreground the contextual and ethical elements back into statistics (e.g., D'Ignazio & Klein, 2020; Taylor, et al., 2020; Rosenberg & Jones, 2022). I situate this lesson at the intersection of current data visualization research and data-justice research to highlight the importance of this intersection in pushing the field of data science learning.

This research is focused on answering one overarching question: *How can educators use data visualizations to build data-wisdom?* Through the exploration of this question, I also developed two sub-questions: 1) *How can educators use data visualizations to establish classroom norms?* and 2) *How can educators use data visualizations to build mathematics confidence?* The nature of data science and how I define it more specifically in this study will be explored in the literature review with special attention paid to the current state of data science education in America, types of data visualizations, and what it means for students to practice data-wisdom.

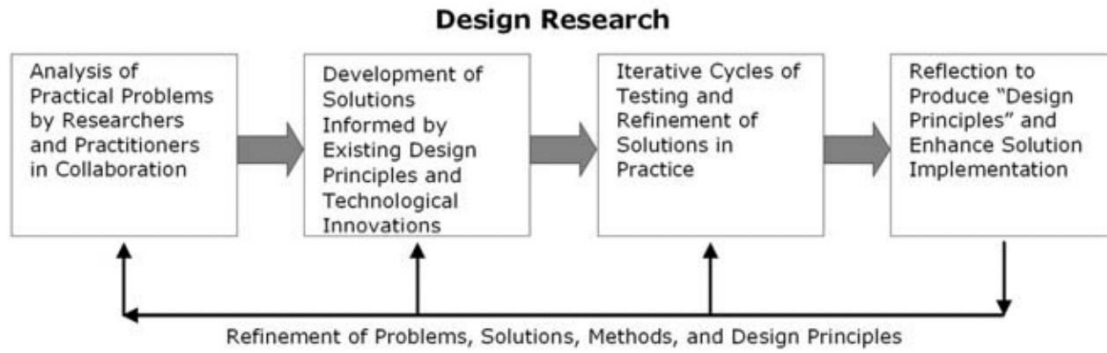


Figure 1: Reeves' (2006, p. 56) Design-Based Research Model

CHAPTER TWO - LITERATURE REVIEW

This chapter focuses on reviewing the literature relevant to building data-wisdom as a data analysis practice and provides a conceptual framework for examining the development of data-wisdom practices in study participants. First, I will motivate the need for data-wisdom by providing a background on how statistics education came to be and more recent calls for the incorporation of data science into statistics education. Within this, I will explore how data visualizations, in particular, offer a unique opportunity for student voice to emerge. Next, I will motivate the need for data-wisdom practices by examining the call for a more humanistic stance in data science education (Lee, et al., 2021). Finally, I will use the data-wisdom practices as described in Taylor & Shea (under review) to provide the conceptual framework needed for this study.

From Statistics to Data Science Education

Statistics education began in the 1920s in the United States (Scheaffer & Jacobbe, 2014). At the time, there was pressure from industry and businesses to teach students statistics because of statistics' expansion into other fields like the sciences and social sciences. Although there was great hope for the expansion of statistics education in the United States, the Great Depression slowed all progress down. 40 years later, in 1968 the National Council for Teachers of Mathematics (NCTM) created a joint committee with the American Statistical Association (ASA) to lead the development of educational materials with a focus on statistics. It was not until the 2000s that the College Board and the National Assessment of Educational Progress (NAEP) included statistics as key measures for college success. In 2007, the first version of the Guidelines for Assessment and Instruction in Statistics Education (GAISE; Franklin, et al., 2007) was adopted by the ASA for curricular use. In 2020, the second version of this report was released and contained the first official call for data science education (GAISE II; Bargagliotti, et al., 2020).

Traditionally, statistics is taught as a set of definitions and operations without meaning behind the application of the concepts (Bajak, 2014). In K-12 education, for example, students are expected to master technical skills such as calculating the mean, median, and mode, and interpreting their meanings relative to the dataset provided.

Sometimes, students are also given a bar chart or some other traditional graph with the same expectations as the core calculations listed above. An additional critique of current statistics education is the lack of incorporation of “big data.” As mentioned, this is a term that was coined to represent the volume, variety, and velocity of modern data production (Laney, 2001) that has become a defining aspect of contemporary life. As big datasets become more accessible, and data-based arguments are increasingly used to understand phenomena and to persuade in the context of public policy debates (Bhargava et al., 2015), it is important for individuals to possess skills beyond the technical skills that currently dominate statistics education.

Data science is often described as thinking through and with data. As scholars note, teaching students how to use data for “personal, civic, esthetic, and emancipatory purposes” (Stornaiuolo, 2020) is and should be the priority. Lee et al. (2021b) describe a framework for data science education that argues for consideration of the personal, cultural, and socio-political layers of individuals’ experiences. Relatedly, Jer Thorp (2011) has said that any attempts to interpret or communicate data trends must be meaningfully connected to their real-world origins. The stories data hold need to be apparent so audiences can understand the relevance and impact of the numbers in a meaningful way. This communication Thorp references is a critical component of data science education.

Why focus on data visualizations?

One strategy for teaching data science is to take a transdisciplinary approach. As opposed to an interdisciplinary approach where themes are designed to cut across content areas, transdisciplinary teaching starts with a problem to solve and, “through the process of problem solving, bring to bear the knowledge of those disciplines that contributes to the solution or resolution” (Meeth, 1978, p. 10). These problems are often situated in real life, rather than the academic study of a particular discipline (Kreber, 2009). Specifically, the combination of data science and art can engage students in the empathetic process that the arts hold (Johnson, 2017) in the context of data sensemaking and argumentation. In recent literature, this takes the form of student-created artistic data visualizations, a digression from the typical charts and graphs often seen in current statistics education

(e.g., Bertling, et al., 2021; Galbraith, in press; Stornaiuolo, 2020). A key component of student-created data visualizations is that students are given the opportunity to choose a personally meaningful dataset. Bhargava et al. (2015) find this approach allows for students to be story finders and storytellers, essential elements in creating citizens that are capable of perceiving and communicating trends in data.

Research also suggests that when students are given authorship over data and their representations, they view themselves as capable data producers and consumers (Stornaiuolo, 2020). These students become agents of data, rather than objects of it, a distinction that has great emancipatory effects, as evidenced in her study and others (e.g., Matuk, et al., 2021; Potapov, et al., 2021; Rubin, 2020). Using personally meaningful data allows students to see the connections between data and their lived experiences, which provides a large opportunity for students to use their voice in combination with data.

When creating a lesson centered around student-created data visualizations, it is important to differentiate between various types of data visualizations. First, there is data-inspired art (Hunter, n.d.). These visualizations notice patterns in data, but their representations often lack contextual elements that aid the reader in understanding the details of the embedded data. Second, there are data-informed visualizations. These creations notice trends and patterns and make the context clear for readers. No single type of data visualization is more valuable than the other, but for this study, we focus on data-informed data visualizations. Participants in this study likely have not been exposed to artistic data visualizations, so having a clearer connection between the data and data visualization was important to highlight the power data visualizations can have in story finding and storytelling.

The Need for Data-Wisdom Practices

The emergence of data science in K-12 settings offers a unique opportunity to redefine how students learn about and use data. No longer is it acceptable to teach students to merely collect, analyze, and synthesize data, but rather this is a time when students must learn about the personal, social, and political layers data contains (Lee, et al., 2021b). The preK-12 Guidelines for Assessment and Instruction in Statistics

Education (GAISE II) promote “statistical literacy for all” but do not consider the inequities that are structurally embedded in statistical practices that harm those from marginalized groups (Benjamin, 2019; D’Ignazio & Klein, 2020). Although it is known that these inequities exist, rarely does the call for expansion of data science education move beyond students learning how to use technologies and programs (Kahn, et al., 2022). The foci of data science education should be that of honing decision-making skills, interpretation skills, and the use of those skills to promote social justice. For this paper, I use Salwell’s (2013) view of social justice. This view 1) recognizes differences while also maintaining fundamental human rights, 2) challenges the distribution of resources, and 3) assumes power is unequal and that power imbalances are reproduced.

A Humanistic Stance Toward Data Science

In examining the current GAISE II standards, the emphasis is clearly on traditional technical skills such as posing a question that can be answered with data, data collection, data interpretation, and data representation (Bargagloitti, et al., 2020), all of which typically focus on firsthand data. While these skills are fundamental to learning statistical processes, students are now interacting with more secondhand data and in increasingly personal ways (Lee, et al., 2021b). This new interaction with data adds a layer of complexity to data analysis that was previously not important. Now, understanding the story behind data and data visualizations is imperative. Remaining in the realm of traditional technical skills removes space for political or ethical considerations (Bhargava, et al., 2015) and the critique of data, data practices, and consideration of the context of data (Philip, et al., 2016). Without incorporating the aforementioned considerations and critiques of data, society will continue to use data in ways that reproduce oppressive and racist technologies, such as facial recognition (Del Villar & Hayes, 2021), algorithms used for healthcare or job applications (Epps-Darling, 2020), and housing opportunities (Akselrod, 2021).

Lee et al. (2021b) stress the importance of recognizing the intersection of the personal, cultural, and sociopolitical layers that are distinct yet overlapping layers within one’s interaction with data. The personal layer is comprised of the immediate personal aspects of data, including their experiences, interests, and prior knowledge. These aspects

directly inform how a student would reason with a dataset. In practice, this layer could include students posing questions for data analysis, designing experiments, or creating visual representations of data. Most importantly, a student's personal knowledge of a dataset increases their ability to access prior knowledge to partake in data analysis more meaningfully (Lee, et al., 2021a). The cultural layer is informed by the tools and cultural practices that guide and maintain a community. Oftentimes, students are asked to complete statistical analysis in programs such as Excel. Although Excel is a powerful tool for students, it can also limit their abilities to reflect on the analytical process and the creation of more artistic data visualizations, an outcome that limits their ability to effectively tell a story about their data (e.g., Lupi & Posavec, 2016). Finally, the sociopolitical layer encompasses the various power dynamics that perpetuate data. At this layer, students must develop a critical eye toward the ways in which data are used to promote or impede social justice. This is the layer where students can practice their civic engagement. Although this is traditionally the least studied layer with students, recent studies have begun to explore the political nature of data and how the interaction with data can be more than authoritative (Lee, et al., 2021b).

Data is about people and people have feelings and action is often catalyzed by feelings. Yet, we find that even justice-oriented data scholars tend to favor thinking over emotion and felt experience as motivation for action (Kahn, et al., 2022). Kahn et al. (2022) expand upon Lee et al.'s (2021b) work by positioning feelings and action as central aspects of data science (see Fig. 2). They begin with the foundational questions "What do you notice?" and "What do you wonder?" but rather than use these questions to prompt mathematical sensemaking, they use these questions to prompt questions about social justice. They use these answers to inform feelings, action, and reimagination, but in no particular order. They find that students were able to practice notice, wonder, feel, and act, but struggled with reimagine. This is a clear call for more practice in K-12 education of reimagining data science to support social justice. I believe data-wisdom has a place here to serve such a role.

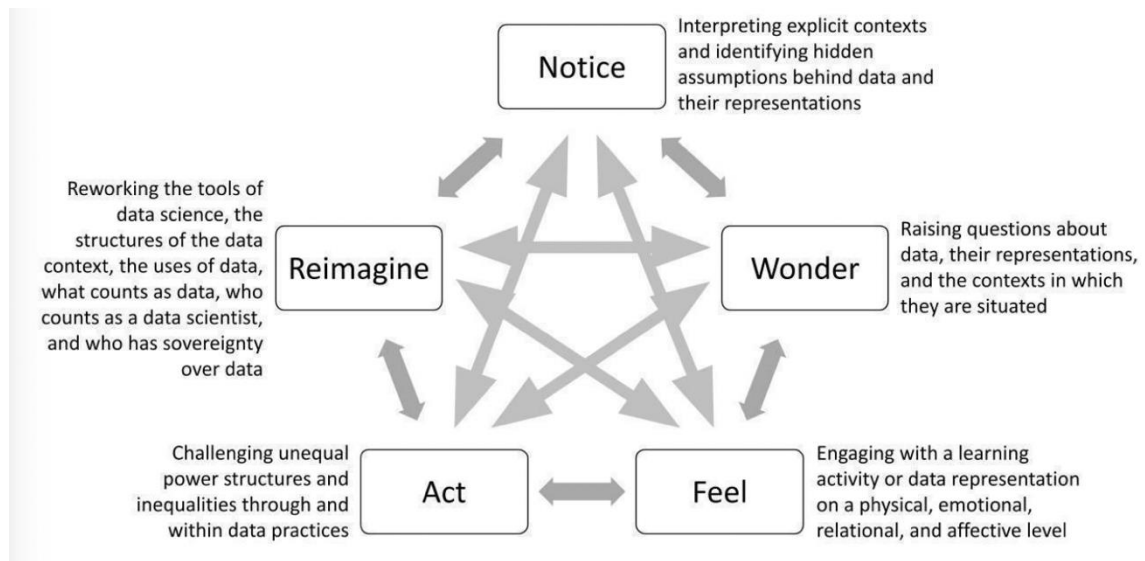


Figure 2: Data Science Reimagined (Kahn, et al., 2022)

Data-Wisdom

So, how do we begin the process of incorporating the humanistic, tri-layer dimensions of data and the importance of reimagining the structures of data science to students' analytical processes? Taylor & Shea (under review) argue we use *data-wisdom* as a guiding principle. From a data science perspective, wisdom requires data users to understand the limitations and dangers of data when using it to inform arguments (Morrison, 2019). Specifically, we must use wisdom to ensure data science is “*personalized, historicized, and actualized*” (Taylor & Shea, under review). For data to be personalized, data users must consider who the data is about and continue to ask about what they still do not know despite the data they currently have (Taylor, et al., 2020). Does the dataset represent the general population? How is the data connected to the people it represents? To be historicized, the temporal narrative of the data must be considered. What global events were occurring or what was the political climate at the time of data collection? Finally, for data to be actualized, data users must use their data analysis for social justice, a call that is met by many of the researchers listed in this section.

Taylor and Shea (under review) suggest three guiding questions to put their data-wisdom principles into action: 1) Data *of what?* 2) Data *for whom?* and 3) Data *towards what ends?* Within each of these three questions, we can ensure data is personalized, historicized, and actualized. I will use these three questions to guide my conversations with participants in each session. Although I do not expect participants to fully realize the depth of these questions, I do believe these three questions are a critical first step in developing the next generation to use data for social justice.

Summary

Big data is embedded in nearly every facet of life making the need for data-wise citizens ever more important. As the call for data science education grows stronger, we must ensure this curriculum includes the incorporation of student voice and skills that aid in analyzing data for civic and emancipatory purposes. Currently, scholars have called for various frameworks to accomplish this goal (e.g., Philip, et al., 2016; Rubin, 2020; Stornaiuolo, 2020), but I suggest that data science should be taught with a data-wisdom

framework (Taylor & Shea, under review). This framework offers students the freedom to simultaneously connect data to themselves and their community, a key element of understanding all layers of data (Lee, et al., 2021b).

CHAPTER THREE - METHODOLOGY

The overall purpose of this study is to examine how the discussion around and creation of artistic data visualizations leads to a deepening of data-wisdom within participants. This study is design-based research intended to guide secondary mathematics educators on how they could begin to build data-wisdom within their students. Descriptive data were collected using a survey, recordings of classroom conversations, and student-created data visualizations. The data were analyzed using a theoretic thematic analysis approach (Braun & Clarke, 2006) under a creative data literacy framework (D'Ignazio, 2017).

Design-Based Research

Design-based research is one of the key methodologies in learning sciences research as it allows for research to be situated within a real educational context (Anderson & Shattuck, 2012; Brown, 1992; Cobb, et al., 2003). Ann Brown (1992) was the pioneer of design-based research—or design research—noting that when conducting research in an educational setting, researchers are responsible for all changes that may be present—from the role of the teachers and students to the type of curriculum (p. 143). Conducting research in any classroom will face a similar but widely varying challenge: the classroom. Each classroom is filled with different students, led by different teachers, with access to differing resources. In order to properly ensure the intervention works for an average classroom setting, researchers must conduct research in a typical—that is, lived and messy—classroom, as opposed to a controlled environment in a laboratory setting. Brown notes that conducting research in this manner does force the researcher to give up some experimental control, but the gain is true richness and reality of how students learn (p. 152). A key characteristic of this methodology is that the research, curriculum design, and learning are interconnected (Cobb, et al., 2003)

Barb & Squire (2004) list four main elements of design-based research. First, the research must produce new or improved theories about teaching and learning. Next, there must be an intervention tested. These interventions must be grounded in appropriate theory while also being practical for the average classroom (Brown, 1992, p. 143). Third, the research must take place in a naturalist setting. Educators are only willing to adopt

new practices when they see that the practices will work for their classroom (Anderson & Shattuck, 2014). Finally, the research process must be iterative. In each iteration, researchers must systematically adjust various aspects of the design to test and create theory.

The focus of this thesis is to understand how secondary students build data-wisdom through a lesson exploring artistic data visualizations using design-based research. To accomplish this, the data-wisdom lesson was created and implemented in two classrooms, allowing for improvements to be made to the instructional materials between sessions. The iterative process focused on improving how the data-wisdom guiding questions were presented. In the first session, participants were expected to be ready to discuss sometimes deep and complex questions in their first introduction to an artistic data visualization. In the second session, students were eased into these questions a bit more by first focusing on how the participants connected to the data visualization before moving into how the data visualization fits in the data-wisdom framework.

Context

This study was implemented during a summer internship program in 2022. The program is designed to recruit and prepare future STEM educators. There are two groups within the summer internship program. The first group is comprised of high school students who have shown an interest in becoming STEM educators after attending college. The second group of students were current undergraduates majoring in a STEM field such as chemistry, mathematics, biology, or computer science. The internship was created to address the shortage of STEM educators in the Southeastern Appalachian area.

The internship is held at a large, public university situated in East Tennessee. In both programs, participants met daily over the course of 4 weeks. For the high school participants, the first week emphasized learning different STEM activities and pedagogy, the second week was centered on leading sessions with a middle school summer STEM camp, and the final two weeks returned to learning about STEM and the intersection with teaching. The undergraduate participants spent their time learning about teaching as a profession by interviewing local educators and education professors. They also planned

computer science lessons for elementary students, created activities for the high school STEM summer camp, and created lessons using the newest technology for their fields.

Rationale for Context Selection

This group of participants was selected in part due to easy access and an Institutional Review Board (IRB) approval plan in place. In addition, and importantly, this group's desire to become STEM educators was also of interest. The lesson the participants participated in is one they can potentially use when they are in their own classrooms, especially as the demand for data-science education increases across all disciplines.

Participants

The participants in the first session were rising high school sophomores, juniors, and seniors, aged 15-17. They all expressed an interest in pursuing a STEM major once they graduated from high school, although their comfort with mathematics varied. Of the five participants in this session, there was one Black participant, one African American and Black participant, one Asian American and Polish participant, and two white participants. The participants of the second session were rising junior and senior undergraduate students, with one additional participant having just graduated from their undergraduate studies. Of the six participants, three were majoring in mathematics, two were majoring in biology, and one was majoring in chemistry. There were five female participants and one male participant; four are Black, one is Latino, and one is white. All participants, with the exception of the participant who had just graduated, were working towards a minor in education with the hope of becoming secondary STEM educators.

Positioning of the Researcher

I have experience as a secondary mathematics educator, and I am very passionate about the importance of data science education at the secondary level. As part of this, I also see a large need to overhaul how mathematics is taught to students in America. I am also involved in the DVP grant that examines the benefits of implementing an artistic data visualization curricular unit with middle school students. Because of this, I was careful to note when I felt my biases were leaning more towards strictly seeing the

benefit in the lesson. Throughout the data analysis portion of this study, I tried to address this concern by being attentive to areas where the class discussion did not go as intended.

Data Collection

The data for this study were collected through a pre-class survey, classroom recordings, and participant-created data visualizations.

Pre-Course Survey

The purpose of the pre-class survey was to collect data about participants' feelings toward mathematics. It also served as a way to encourage participants to think in a more mathematical sense because leading up to this lesson, they had been much more focused on other topics like teaching methods. The survey was comprised of 18 Likert-type questions (e.g., "After I study a topic in math and feel that I understand it, I have difficulty solving problems on the same topic"), which were adopted from the Mathematics Attitudes and Perceptions Survey (MAPS) (Code, et al., 2016). Participants were asked to share information about themselves related to growth mindset, real-world application, sense making, and confidence, all of which are essential habits and skills when working with data (see Table 1²). After participants completed the survey, there was a class discussion about their responses that included questions about why they selected the answers they did and if those responses make them more of a "math person" or not.

Classroom Recordings

The purpose of the classroom recordings was to collect detailed responses from the participants surrounding their discussions of the data-wisdom guiding questions (see Appendix B) and their perceptions towards the analysis of data visualizations. Between the two iterations, approximately 100 minutes of conversation were recorded and analyzed. I obtained verbal consent for recording our conversations from all participants before the recordings began. Only audio recordings were collected.

During the class discussion of the data visualizations, I used a semi-structured interview protocol. To begin, the questions were broader in nature. I asked participants

² All tables can be found in the Appendix.

what the data visualization made them think of and how the data visualization would change if they were to recreate it in their neighborhood. Next, participants began to consider who the artist of the data visualization was. Participants discussed what they learned about the artist and how the participants might be similar to or different from the artist. Finally, participants were asked to consider how the data visualizations might be different if someone in a rural part of the state were to create them. In all of these questions, participants began to consider who is the data about and why is the data being presented in a certain way.

Although there was a set selection of questions, conversations largely followed what the participants thought was important to discuss based on their reactions to the data visualization and the class discussion. There were times that I needed to redirect the conversation, but largely I left it up to the participants. After the two sessions were completed, I completed all transcription of the recordings manually. There are sections of recordings where the conversation is unintelligible.

Participant-Created Data Visualizations

At the end of the lesson, participants were asked to collect data on themselves for a set amount of time and then create their own artistic data visualization. They were given the option to collect data for one day or one week depending on what they wanted to represent in their data visualization.

Data Analysis

Data were analyzed using theoretic thematic analysis as described by Braun and Clarke (2006). Thematic analysis is used to organize and find patterns within a given set of qualitative data with the benefit of not necessarily being tied to a specific theoretical framework (Braun & Clarke, 2006). The selection of theoretic over inductive thematic analysis is due to the specific interest in how participants build data-wisdom based on the questions that were asked during each session.

Following Braun and Clarke's (2006, p. 87) steps, I followed three phases of analysis. In the first phase, I first transcribed the data and noted initial themes I saw emerging from the data. I made note of conversations that were particularly powerful for individuals and the group as a whole, noting times when students were being pushed on

their ideas of what data visualizations are and how they can be analyzed using data-wisdom practices. For example, in the first session, participants were discussing how an artist spent her time throughout the week. Rather than allowing participants to stop their analysis with only the consideration of the author, I pushed them to consider how a data visualization like this might encourage them to change their own behaviors—pushing *data towards what ends*. In the next phase, I read through the transcript three times, each time making new notes of codes in the margin. During this phase, I noted when I redirected conversation or my presence seemed to shift the conversation. I was attentive to participants mentioning their own experiences with data, data visualizations, and the subjects of each data visualization.

Finally, after spending time with the codes from the transcript analysis, I organized the codes theoretically and noted connections between some themes, creating a thematic map as described in Braun and Clarke (2006, pp. 90-91). In this process, I made sure to keep the development of data-wisdom as the focus of my analysis while working within the creative critical data literacy framework. Themes were named using the principles of data-wisdom (Taylor & Shea, n.d.) in a concise manner (i.e., “whom,” “what,” and “towards what ends”). Finally, I extracted quotes and excerpts of conversation that highlighted the themes.

In summary, I used the classroom recordings to address the overarching question, “How can educators use data visualizations to build data-wisdom?” The recordings were transcribed and analyzed using an iterative thematic analysis process. To address the first sub-question, “How can educators use data visualizations to establish classroom norms?,” I used the classroom recordings and followed the same process before, with special attention paid to turn-taking and participants’ personal connections to the data. To address the second sub-question, “How can educators use data visualizations to build mathematics confidence?,” I used the pre-course survey, which was analyzed for participant perceptions towards mathematics, and the classroom recordings, where I looked for participants making positive remarks about the activity. A summary of the data collected and data analysis for each research question can be found in Table 2 in the Appendix.

CHAPTER FOUR - INSIGHTS GAINED

The insights gained from this study are presented below, broken into three main themes: 1) data visualizations to build data-wisdom, 2) data visualizations to establish classroom norms, and 3) data visualizations to build mathematics confidence. The data for all three sections come primarily from the classroom recordings, with particular attention paid to student comments. I contrast students' closing comments about artistic data visualizations with the pre-intervention survey results to highlight the difference in opinion of math generally and their experiences exploring data through data visualizations.

After completing the first iteration of this lesson with the high-school participants, edits were made to the flow of the lesson before I implemented the lesson with the undergraduate participants. Particular attention was paid to the order in which guiding questions were asked and when it was appropriate to dig deeper into the data-wisdom principles. I found that starting the undergraduate session with more basic and familiar questions in the first data visualization offered more opportunities for deeper conversations about data-wisdom in the subsequent data visualization analysis.

After analyzing three artistic data visualizations with the two groups of participants, there were a few common themes that emerged. First, participants required more probing than anticipated to answer the data-wisdom questions. By the third data visualization, however, participants were able to answer, "*Data of what?*" on their own. Next, both groups of participants felt it was hard to "see" the mathematics in the data visualizations. It was not until I spent time connecting the key to the data that they began to understand how to represent data in a nontypical way. As expected, with intentional probing and practice analyzing the data visualizations, the participants' abilities to meaningfully apply the data-wisdom practices improved. In the results below, I will look more closely at the evidence that suggests the exploration of artistic data visualizations with specific guiding questions creates opportunities that can begin to support the development of data-wisdom practices in students.

Data Visualizations to Build Data-Wisdom

For this study, I focused on teaching the three data-wisdom questions posed by Taylor et al. (2020): “Data of what?”; “Data for whom?”; and “Data towards what ends?” To accomplish this, I walked students through the exploration of three artistic data visualizations created by Giorgia Lupi and Stefanie Posavec (2016). In each session, students were given time to think about what they believed the data visualization represented—first without seeing the key—followed by a small group discussion and then a whole class discussion. In these discussions, students were encouraged to share how they believed their interpretations might be influenced by their own situated context and/or upbringing. I asked guiding questions to encourage the consideration of data-wisdom practices.

Data of what?

To consider “data of what” in a data visualization, I anticipated that participants would be able to answer what dataset was used to create the data visualization and how the temporal component of data collection might impact the final presentation. Once participants became comfortable identifying the dataset the author was using, I felt comfortable pushing them to consider the deeper, temporal dimension of “data of what.” I did this by moving beyond the elementary question “what dataset is used in this data visualization?” to more complex questions about how the temporal and spatial components of data collection can contextualize the stories data are telling.

Given that this was the first time students were being introduced to data-wisdom practices, I sought to keep the guiding questions simple. To begin, I asked the question, “what dataset did (the author) use to create this data visualization?” Initially, participants in both groups were unsure of how to answer this question, with one participant in the high-school session saying, “This is not math. There are no numbers represented in this image.” Another participant who struggled to see math in the data visualization said, “I’m so used to thinking of numbers and integrals with math. It is hard for me to think of math without those present.” As the conversation went on, it became easier for participants to identify what dataset the author was using to create the data visualization. In examining the second data visualization (see Fig. 3), the high-school participants were quick to point



Figure 3: Posavec's Data Visualization of Time Spent. (Dear Data, 2016).

out that “this is math” because they could see how Posavec integrated the math concept of frequencies by creating flowers that represented how her time was spent.

To address the temporal component, participants were asked to compare how Posavec’s time spent data visualization (see Fig. 3) would compare to their own version. This consideration asks students to compare the phase of life they are in to the phase of life Posavec is in. For the high school participants, they noted they would have much less time at work and an additional category for school. With the undergraduate participants, we spent time discussing how Lupi’s representation of apps on her phone (see Fig. 4) might change if it were created today. Participants thought of apps for ridesharing, online food ordering, and virtual meeting spaces like Zoom that Lupi does not represent but that are important in today’s world.

To address the spatial component of data collection, I asked participants to consider how Lupi’s app data visualization might change if it were created in different areas around Tennessee.

Teacher: How do you think this data visualization would change if I were to compare this data visualization to someone in rural Tennessee?

Tyra: I feel like they would definitely have a lot more games.

Sara: There probably would not be a Sonic app.

Olivia: Probably not the Capital One app. Might be a little hard to get approved in a rural area. Did they have any rideshare apps?

Teacher: Great question!

Haley: I feel like the bigger apps might not work in rural communities because you don’t have as much access. My grandparents have Facebook and they use the photos and that is it. They grew up rurally, so they don’t need a lot.

Sara: With the new update, you can take apps off the home screen, so that could change this, too.

Tyra: I feel like the type of phone would change this because not everyone can afford an iPhone.



In this vignette, we see that the undergraduate participants are aware of the differing needs across communities and differing socioeconomic realities for urban and rural communities. More importantly, they are developing an awareness that data can be collected in ways that are biased, that is, they do not reflect the population as a whole. These awarenesses are critical when looking at data and data visualizations with a critical, data-wisdom eye.

Data for whom?

To consider “data *for whom*” in a data visualization, I expected participants to consider who the data is about and who is using the data by examining the data visualization within the context of the author’s life. When examining this aspect of data-wisdom, I expected participants to consider what they still did *not* know after examining the data, rather than assuming they knew everything about the subject(s) of the data visualization. For the participants in this study, we began by considering who the subject of the data was and what story the data visualization can tell us about that subject. To highlight this, here is a vignette of a conversation in the undergraduate group:

Teacher: What do we know about this woman now?

Olivia: She gets on Instagram a lot. I can tell that because the “how often do I use it” representation for that app is hourly. She uses it hourly. You can also see that she is checking her bank account regularly.

Teacher: Interesting. So maybe she is money conscious?

Tyra: I feel like she has an important job because she doesn’t have a lot of games. Even though I am in college, I still have like six games on my phone that I regularly use. It could be that she is an adult.

Olivia: I find it interesting that she has her Instagram separated from everything else.

Sara: Well it could be that her job is something with social media because her Twitter is also pretty high along with her messages and emails. I know that when social media is your job, you are constantly getting emails and messages.

Participants began thinking about who Lupi is. Does she work in marketing or social media given her use of Instagram and photos? Does she attend a lot of events given the importance of the maps app? Based on the number of banking-related apps, how money conscious is she? All these questions are considering what we still do not know about Lupi.

Data towards what ends?

“*Data towards what ends*” is the pinnacle of the data-wisdom and social justice movement within data science education. This question requires readers to determine if the data and accompanying data visualization are being used to create a more just society. This is a big question for teenagers to answer, but not one that I believe they are incapable of answering. I expected participants to be able to take the given data visualization and think about if that data visualization or one they could create would make a change in their own life or someone else’s life. To introduce participants to the idea, I asked students if they thought a visualization like Posavec’s representation of her time (see Fig. 3) would change the way they spent their time. Although this is not explicitly asking students what the broader impact of this data visualization is on society, it does require them to begin to think about the effect a data visualization might have in their life or others. In this reflection process, one participant from the high-school group stated that if they created a similar visualization, it might become clear that they “need to spend less time on social media or their phone, generally.” It is important to note that participants did not arrive at considering *data towards what ends* on their own. It was not until I asked the high-school group, “Do you think this could impact the choices you make in your life after you collected this data?” for them to think about the data visualization beyond what was explicitly presented. I did not ask this type of question with the undergraduate participants and there was no real discussion of the implications of data. I will discuss more of what this can mean for teachers in the discussion.

Data Visualizations to Establish Classroom Norms

In this project, there were two central norms I focused on: thinking deeply and engaging in meaningful discourse. I define thinking deeply as the ability to think beyond the information that is given. This can be interpreting results beyond the obvious or

applying concepts to different situations. Engaging in meaningful discourse is defined as participants sharing their thoughts about the mathematics presented with their peers and classroom community. I chose to focus on these two norms because of their importance in learning mathematics and applying those skills beyond the classroom. In the context of data visualization analysis, thinking deeply asks students to analyze elements in a data visualization and connect to some of these elements. In doing so, they are immediately moving beyond the raw data and considering the humanistic aspects of data. Also, NCTM's Principles, Standards, and Expectations (NCTM, 2000) states that students should be able to communicate their mathematical thinking clearly to others and critique the mathematical thinking of others. Both of these skills are essential when story finding and storytelling with data.

To encourage thinking deeply in this study, I asked participants to find elements of the data visualization they connected with. This step immediately pushed participants to think beyond numbers and the statistics behind those numbers. In doing so, participants must analyze why an artist would choose to use certain elements, how those elements might be connected back to the data, and what story is the author trying to tell. How this practice came to life in the study can be illustrated in the discussion of Lupi's apps and her representation of use. In this portion of the discussion, participants connected to the representation of the apps but wondered what the surrounding elements were. They determined that the red dot represented notifications, the lines surrounding the app represented folders, and the organization was based on the layout of her phone. They also crafted a story about Lupi, which would not have been possible without thinking deeply beyond the visible aspects of the data visualization were and what those aspects reflected about Lupi.

Regarding meaningful discourse, by taking the obvious mathematics out of this activity, I found that participants were more willing to engage in discourse and connect with their peers. In my past experience as a secondary mathematics teacher, it was not uncommon for the majority of my students to not respond when discussing new ideas. With this activity, however, I found all participants were willing to talk about the connections to the data visualizations, connections with their peers, and how mathematics

is intertwined into all of those aspects. Engaging in meaningful discourse requires a comfort level with making comments and asking questions as a starting point. From here, conversations can continue to build on and extend initial contributions.

Data Visualizations to Build Mathematics Confidence

Building mathematical confidence was not the overarching research question of this study, but I find it to be an important result to mention. From the pre-survey, I found that 50% of all participants only learn math when it is necessary and that 67% of high school participants and 100% of undergraduate participants are not confident when taking math tests (see Table 1). At the end of each session, I asked participants if analyzing data visualizations changed their perspective on mathematics in any way. In the high school group, participants noted that they were able to see the story the data was telling, rather than just a collection of numbers. Multiple participants in the undergraduate group stated that viewing an artistic data visualization made it easier for them to “see” the numbers, rather than having the data presented in a typical table or graph. One participant stated, “I think something like this would help a lot with kids who are like me and numbers are hard for them to make sense of.” Another participant stated that viewing artistic data visualizations makes it easier to connect with the data and see its value in more areas of life.

CHAPTER FIVE - DISCUSSION AND IMPLICATIONS

Data science is the next generation of statistics education in America. As technology becomes increasingly powered by big data, there are new demands for people to manage these systems (IES, 2021). Typically, the focus of data science is the intersection of mathematics, computer science, and industry-specific knowledge, but we must also address the ever-growing concern of exploitation through data (D'Ignazio & Klein, 2020). Teaching data science within the framework of data-wisdom requires data scientists to consider who collected the data, whom the data is about, and how the data is being used to communicate specific narratives (Taylor & Shea, n.d.).

The purpose of this study was to explore how students can practice data-wisdom techniques through the exploration of three data-informed data visualizations. As a secondary outcome, I explore how data visualizations can be used to improve participants' perceptions toward mathematics in general and establish classroom norms. Design-based research is used from the first session to the second to allow for critical changes to the order of presentation of questions and the follow-up questions asked by the researcher. The second session of the lesson did have some advantages including allowing more time for students to connect personally to the data, but both sessions show glimmers of data-wisdom practices being utilized by participants.

To evaluate if participants were using data-wisdom practices, I analyzed transcripts from each session to find where participants discussed any of the three foundational questions. I found that each of the three data-wisdom foundational questions were addressed across the two sessions. Although it is too far of a jump to say that participants fully developed data-wisdom, the questions presented by Taylor & Shea (under review) seem to support opportunities for developing data-wisdom practices in secondary and post-secondary students. We can see this opportunity highlighted in how participants began to consider the underlying dataset, how time can change the display and interpretation of data, and how they might use a data visualization to change their own behaviors.

Given that the post-secondary participants were all in a teacher preparation program, I find it essential to discuss the importance of a broad implementation of data

science for social justice. Currently, much of the talk around data science is in the K-12 space, but in order to effectively implement a data science unit, the classroom teachers must have the appropriate content knowledge. Professional development is one option for in-service educators, but in order to make a substantial change, a more robust learning opportunity for pre-service educators is needed. These pre-service educators must be equipped with the appropriate background knowledge of data science *and* the knowledge of how to use data science for emancipatory practices. If attention is not paid to pre-service educators, an effective data science curriculum implementation could be nearly impossible.

I also found that exploring data visualizations provided a lower threshold (NRICH, 2019) into data analysis than if I were to have given them a complex dataset or typical data representation. Participants said viewing data as a more artistic representation created the opportunity for them to connect the data back to their own lives. They also stated that they felt more willing and able to analyze the data presented because they did not feel the initial anxieties sometimes felt when looking at data.

Limitations

Although I find participants were able to start using data-wisdom practices, it is only a start. Ideally, this would be a curricular unit implemented over a longer period of time. This would allow students to make deeper connections between datasets, data visualizations, and the implications for society as a whole. The connections students made were largely surface-level and did not extend much beyond their personal experiences and close community. I was also unable to select data visualizations that were of personal interest to any of the students because I did not know who my participants were. I believe if I would have been able to select more meaningful data visualizations, the data-wisdom discussion likely would have been richer.

Allowing for more time would also provide the opportunity to make this lesson—or unit—truly transdisciplinary. The creation of data visualizations follows the design process that is present in both mathematics and art. Combining these two subjects has the potential to bring humanity into a subject that is traditionally lacking that component (Maeda, 2013).

Additionally, my background and experience in this space afforded me the ability to ask guiding questions of the participants that educators implementing data-wisdom practices for the first time might not know to ask. To anticipate student questions, it is important to have a level of understanding of the data visualization and of data-wisdom practices as a whole. In Table 3, I have provided a set of questions that I believe are a great starting point for exploring data-wisdom in K-12 classrooms. Given that the majority of students have not had practice data-wisdom, the questions are relatively elementary. It is my hope that these questions will start a data-wisdom discussion that becomes more fruitful.

Finally, I believe that the number of participants I had and the interests of both groups do not represent a typical mathematics classroom. In total, there were 12 participants spread across two sessions. Apart from rural and small school districts, I do not believe it would be capable to find a classroom with this few students. Having a smaller number of students can make the lesson implementation easier because it is easier to individually interact with each student. The participants in each group were also part of a STEM internship. Each of these students is likely more successful in their STEM disciplines than the average student and likely has a greater interest in mathematics than the typical American student. This could skew the results of students' abilities to analyze the data and extend their interpretations beyond typical expectations. I found that all students were willing and eager to engage in conversation, but I do question if this would be the case in a typical mathematics classroom.

Future Research

Currently, there is a lot of research being conducted in the data science space. Two of the most available are by Jo Boaler, who has created data science lesson plans for K-12 teachers (YouCubed), and Michelle Wilkerson, who has created lesson plans to address statistical literacy using data science (Writing Data Stories). Neither of these resources, however, addresses the societal implications and social justice power of data analysis and data visualizations. However, there are two research projects that are more focused on the transdisciplinary aspect of data visualizations while also creating a strong connection to the community. I believe it is projects like these with a strong emphasis on

how data can be used for good that will push the field of data science in K-12 education to the next level.

In conclusion, I find that incorporating the humanistic aspect of data back into data science can be accomplished by using data-wisdom practices. As big data becomes the standard and decisions are increasingly made based on big data, remembering who the data is about and how we can use it for social justice is key. This movement should start with current K-12 students as they are the future of data science.

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APPENDIX - TABLES

Table 1: Relevant Pre-Survey Results

Questions	Response					Session
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	
There is usually only one correct approach to solving a math problem.	0%	17%	0%	17%	66%	1
	0%	0%	0%	33%	67%	2
I'm satisfied if I can do the exercises for a math topic, even if I don't understand how everything works.	0%	67%	0%	33%	0%	1
	0%	33%	17%	50%	0%	2
Nearly everyone is capable of understanding math if they work at it.	0%	33%	50%	17%	0%	1
	17%	50%	17%	0%	0%	2
I expect the answers to math problems to be numbers.	0%	67%	0%	17%	17%	1
	0%	17%	50%	33%	0%	2
Learning math changes my ideas about how the world works.	17%	33%	50%	0%	0%	1
	17%	17%	17%	50%	0%	2
No matter how much I prepare, I am still not confident when taking math tests.	33%	33%	17%	0%	17%	1
	33%	50%	17%	0%	0%	2
If I get stuck on a math problem, there is no chance that I will figure it out on my own.	0%	17%	33%	17%	33%	1
	0%	17%	50%	17%	17%	2
I only learn math when it is required.	33%	17%	0%	50%	0%	1
	17%	33%	0%	33%	17%	2

Table 2: Research Question Analysis

Research Questions	Data Source	Data Analysis
How can educators use data visualizations to build data-wisdom?	Classroom recordings	Transcribed and analyzed with multiple iterations of coding.
How can educators use data visualizations to establish classroom norms?	Classroom recordings	Transcribed and analyzed with multiple iterations of coding.
How can educators use data visualizations to build mathematics confidence?	Pre-Course Survey (Table 1); Classroom recordings	Survey was analyzed for participant perceptions towards mathematics; classroom recordings were transcribed and analyzed with multiple iterations of coding.

Table 3: Introductory Data-Wisdom Questions

Data-Wisdom Question	Questions to Guide Student Thinking
Data of what? • Historicized	• What was happening in the world when these data were collected? • What were the societal structures in place during the time these data were collected? • Who is collecting and publishing these data?
Data for whom? • Personalized	• Who is this data about? • Who is using this data? • Are the data collected connected to the communities for which they represent?
Data towards what ends? • Actualized	• How is this data being used? • Are data collectors and publishers following just data collection practices? • Is the data being used to create a more just society?

VITA

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