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The Search for Evidence of Statistical Thinking: How Secondary Education Teachers Reason with Non-Traditional Data

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The Search for Evidence of Statistical Thinking:
How Secondary Education Teachers Reason with Non-Traditional Data

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Science in Statistics

by

Terri Anna Johnson

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ABSTRACT OF THE THESIS

The Search for Evidence of Statistical Thinking:
How Secondary Education Teachers Reason with Non-Traditional Data

by

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Master of Science in Statistics
University of California, Los Angeles, 2019
Professor Frederic R. Paik Schoenberg, Chair

The abundance of *big data* has paved a way for its use in secondary mathematics classrooms. Model eliciting activities with participatory sensing data allows us to determine how well teachers can navigate a statistical investigative process, as defined by the Data Cycle. Video coding helps to map teacher progress through the different phases of the Data Cycle, as well as periods of "stuckness" during a model-eliciting activity.

The thesis of Terri Anna Johnson is approved.

Robert L. Gould

Mark Stephen Handcock

Frederic R. Paik Schoenberg, Committee Chair

University of California, Los Angeles

2019

To Marjie Johnson & Jackie Stytle

the best moms a girl could ask for

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Completing this degree has been the single-most challenging thing I have ever done. It goes beyond saying that I could not have done it without a multitude of people.

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Figures in Chapter 2 were all reproduced with permission by the respective publishers, specifically Figure 2.1 (Box et al., 1978), Figure 2.2 (Wild and Pfannkuch, 1999), Figure 2.3 (Gould et al., 2015), and Figure 2.4 (McCartney et al., 2007).

CHAPTER 1

Introduction

Educators have long anticipated the development of a statistically literate society, and the recent influx of accessible data has made this goal finally seem attainable. However, the immense surge of data brings with it a new challenge for educators. It is no longer sufficient for students and teachers to only be statistically literate in this new age; in addition, they must also strive to be data literate.

As *big data* became an established term in pop culture vocabulary, it simultaneously sparked a need for educating a data literate generation. The ability to use data to tell stories is one of the hallmarks of being a data scientist (Bladt and Filbin, 2013). Data scientists use both statistical and computational thinking to approach empirical problems. The urgent need to foster the development of such a data-minded generation was reiterated when President Barack Obama announced the appointment of Dr. DJ Patil as the federal governments first-ever Chief Data Scientist in February 2015 (Smith).

This thesis serves to motivate research for assessing and evaluating the ability of secondary-level mathematics teachers to think and reason with data. We begin with a discussion of big data and the inability of such data to fit into the traditional statistical paradigm previously used by educators. Data literacy is explained through the context of statistical thinking. A review of deductive video analysis methods is also discussed as a tool for mapping teacher thinking trajectories. These methods will be used to determine if we can find evidence of statistical thinking and data literacy. A brief history of the Mobilize Project steers the discussion towards the eventual development of the Introduction to Data Science (IDS) curriculum, which addresses the critical need for renovation in secondary-level mathematics education.

This thesis aims to answer the following two research questions related to statistics education at the secondary level:

1. To what extent are teachers able to negotiate a statistical investigative process?
2. When do teachers get stuck and unstuck while navigating through a statistical investigative process?

CHAPTER 2

Motivation

This chapter discusses the previous research that has provided a pathway for exploring the research questions mentioned above. Since traditional inferential statistics in secondary school classrooms encourages particular data collection methods (chief among them random sampling), this research diverts from convention in order to explore the roles of both informal and formal statistical inference when working with non-traditional data structures.

The discussion starts with a review of traditional data formats historically used in secondary statistics education settings and transitions into alternative data types that can still allow statistical inference to be done. The history of statistical thinking is explained which segues into model eliciting activities. Lastly, deductive video analysis methods are reviewed and specific software packages are introduced.

2.1 Traditional vs. Non-Traditional Data & Secondary Statistics Education

In the context of formal statistical inference, the use of randomly collected data has historically been necessary in statistics classrooms (Kelly and Lesh, 2000). In educational settings, this standard is used because the existing curricula focus on making formal inferences, in which we need to reduce bias in the measured estimates. Because of this, exploratory data analysis is given little attention in secondary classrooms. Traditional inferential statistics has been the basis for nearly all statistics curricula in secondary education. Statistics courses are widely taught almost exclusively with randomly collected data to ensure that a population is accurately represented in order to meet the strict format required for formal statistical inference. The saturation of the term big data within the last decade has created a necessary challenge to traditional statistics ideology, which maintains the belief that random sampling provides a way through which uncertainties in estimators can be quantified.

While inferential statistics will always be useful and necessary to create a statistically literate classroom, it simply is not enough for a truly data literate one. Students and teachers are inundated by volumes of rich data that constantly record information about them and their surroundings. Because of this, people are interacting with data on a near-daily basis, but have few, if any, tools to begin exploring these data or to make inferences about them. The examples below represent just a small portion of personal information students and teachers routinely (and sometimes unknowingly) share that have provided the abundance of big data available today.

a. Twitter feeds
b. Facebook posts
c. Instagram posts
d. Cell phone usage
e. Google Maps and GPS tracking
f. Credit and debit card usage
g. Photos and videos

The definition of big data has evolved over the past few years. At its conception, the term meant exactly what it sounds like: datasets that were so large in size that special computational tools were required to store, access, and analyze the data. Big data have been defined by a dataset's ability to satisfy one of the "three V's" known as Volume, Variety, and Velocity (Wilder-James, 2012). Volume refers to the scale of the data, variety refers to the different forms data can take, and velocity refers to streaming data. In 2013, IBM introduced a fourth option, Veracity, which pertains to the uncertainty in data (IBM, 2013). As time has progressed, the term big data has become even more inclusive. Lane et al. even refer to big data as its own "paradigm" (2014, pg. 46). It is important to note that data included in this paradigm are not necessarily big in volume. However, they have characteristics that can be mapped to at least one of the other V's, which classifies them as big data. These are the characteristics that distinguish big data from traditional data that have historically been used in statistics classrooms. Data are now considered more than just "numbers with context" (Moore, 1990); in addition to numbers, data now include text, images, sounds, locations, and many more possibilities.

Clearly, this suggests that data are not always random and are definitely not always numerical. It is imperative that we introduce methods to interact with and analyze these types of data to students and their teachers as soon as possible. Although we may not be able to make causal inferences or causal claims about such data, they can still be used as a productive teaching tool for informal statistical inference (Makar and Rubin, 2009). The information obtained from data that are not randomly collected can provide useful information and insights; we just have to be aware of what claims can and cannot be made.

Because big data are rarely collected according to traditional random sampling protocol, statistics educators, especially at the secondary school level, are being challenged with a difficult decision: to keep teaching with historical datasets that remain loyal to the old paradigm, or to bravely cross over into the big data paradigm where data are relatable and easily accessible to each student.

As with almost any new teaching tool, big data are, and will continue to be, challenging to work with in a classroom setting because there is not always mathematical theory to guide us towards formal statistical inference. But at the same time, these data are enormously influential on both our culture and economy, and therefore should not be omitted from use in the classroom. If we refuse to implement change at the secondary school level, the profession of statistics will likely become archaic and even less intriguing to students. In order to create the data literate classroom we desire, students need to connect to the actual practice of statistics.

2.2 Statistical Thinking

This section reviews the evolution of the term statistical thinking and how it has developed into a simplified model referred to as the Data Cycle. Model eliciting activities (MEAs) are introduced as a way to assess and observe statistical thinking.

2.2.1 Defining Statistical Thinking & The Data Cycle

To begin, we discuss the meaning of the elusive phrase "statistical thinking." Over the last 35-40 years, many researchers and committees have attempted to characterize what is meant by the term "statistical thinking."

Some notable contributions were made by Box et al. in 1978 with the publication of their textbook "Statistics for Experimenters." They outlined scientific investigation as an iterative learning process sparked by the need, or want, to solve a particular problem (Box et al., 1978). In order to solve the problem of interest, you first start thinking of ideas that might help and then you look for data that can either support or refute that idea. Figure 2.1 was provided in their textbook as a visual for this iterative process. The continuous cycling between ideas and data are what drives the investigative process.

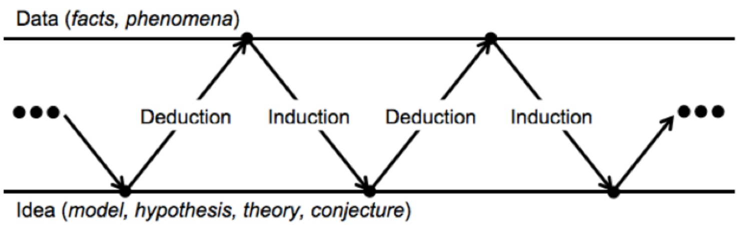

Figure 2.1: The Iterative Learning Process. Reproduced with permission from 'Statistics for Experiments, Second Edition' by G.E. Box, J.S. Hunter, and W.G. Hunter, 1978, p. 2. Copyright 2005 by John Wiley & Sons.

The iterative process is key here in order to find an appropriate conclusion regarding the data. Their approach emphasized the need to incorporate both statistical methods and subject matter knowledge during the *Idea* phase (1978, pg. 6) to find the most effective explanation. Moore (1990) identified the following 5 elements as key aspects of statistical thinking:

a. the omnipresence of variation in processes,
b. the need for data about processes,
c. the design of data production with variation in mind,
d. the quantification of variation, and
e. the explanation of variation.

He emphasized that statistical thinking could be used in everyday life because humans themselves are variable, but that it must be present in curriculum for the skill to develop. During the same year, in the field of quality control, Snee defined statistical thinking as "*thought processes*, which recognize that variation is all around us and present in everything we do, all work is a series of interconnected processes" (Snee, 1990). He explained that opportunities for improvement could be found by

a. identifying variation,
b. characterizing variation,
c. quantifying variation,
d. controlling variation, and
e. reducing variation.

By 1992, Moore's explanation of the process of statistical thinking was adopted by a Joint Curriculum Committee of the American Statistical Association (ASA) and the Mathematical Association of America (MAA) (Cobb, 1992). The following year, another group, the ASA Working Committee on Statistical Thinking (Sylwester, 1993) recommended:

a. the appreciation of uncertainty and data variability and their impact on decision making;
b. the use of the scientific method in approaching issues and problems.

A common theme starts to appear at this point that understanding and explaining variation in regards to a problem is an integral part of successful statistical thinking. Mallows further clarified the definition by explicitly stating that data must be relevant to a real-world problem, "often in the presence of variability and uncertainty" (Mallows, 1998). He challenged statistics education researchers to develop a theory for statistical thinking.

Wild and Pfannkuch rose to the task and have since contributed extensive research to the topic of statistical thinking. Their research differs from the previous examples by observing statisticians and what they do in practice, instead of simply asking statisticians what it means to think statistically (Wild and Pfannkuch, 1999). They emphasized that the use of real-world problems is a crucial component. Statistical thinking occurs when the analysis can be connected to the context of the problem.

In 1999, they developed a four-dimensional framework for the process of statistical thinking. The Investigative Cycle was described within Dimension 1 and introduced the Problem, Plan, Data, Analysis, Conclusions cycle, more commonly referred to as the PPDAC cycle (see Figure 2.2).

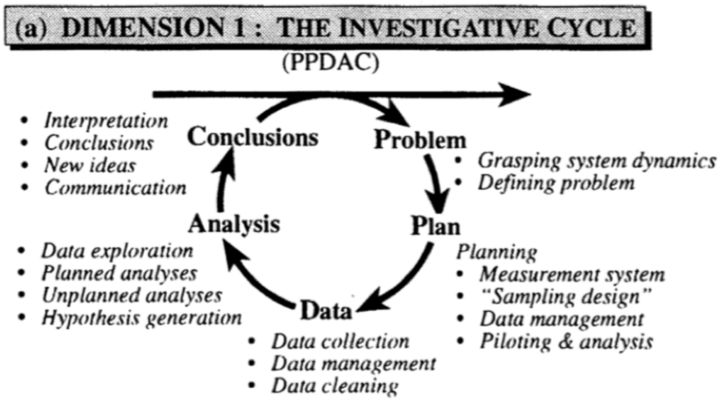

Figure 2.2: The PPDAC Cycle. Reprinted with permission from 'Statistical Thinking in Empirical Enquiry,' by C.J. Wild and M. Pfannkuch, 1999, International Statistical Review, 67(3), p. 226. Copyright 1999 by International Statistical Institute.

In their overall framework, Wild and Pfannkuch laid out 5 foundations of statistical thinking:

a. recognition of the need for data;
b. transnumeration (considering multiple representations of the same data to determine which best elicits understanding);
c. considering variability;
d. reasoning with statistical models; and
e. merging statistical with contextual.

The National Council of Teachers of Mathematics published the Principles and Standards for School Mathematics and identified a Data Analysis and Probability standard for classrooms from pre-kindergarten to grade 12 (2000). The standard recommends that instruction "should enable students to

a. formulate questions that can be addressed with data and collect, organize, and display relevant data to answer them;
b. select and use appropriate statistical methods to analyze data;
c. develop and evaluate inferences and predictions that are based on data; and
d. understand and apply basic concepts of probability."

In order to create a synthesis of all these ideas about what statistical thinking is and how to incorporate it into educational settings, the American Statistical Association formed a committee in 2005 for determining a framework for how to teach it at the K-12 level. The resulting 2007 publication, titled Guidelines for Assessment and Instruction in Statistics Education (GAISE) Report, simplified the process of statistical investigation into four steps (Franklin et al., 2007):

a. Formulate Questions
b. Collect Data
c. Analyze Data
d. Interpret Results

During the Formulate Questions component, students should be able to identify a "problem at hand" and create questions that can be answered with data. Students will be "anticipating variability" as they formulate questions. In the Collect Data part, students begin to "acknowledge variability" by creating a plan on how to collect relevant data for the problem and then use the plan to collect it. The next phase, Analyze Data, should "account for variability" by preparing students to use appropriate graphical and numerical methods to analyze their collected data. In Interpret Results, students should be able to interpret the results of their analysis and then apply their conclusions back to the original problem. This phase "allows for variability." We see that the GAISE guidelines express the need to consider variation at all points of the process.

In an attempt to represent the information contained in the report, the Mobilize project team (see Section 3.1) created a graphic depicting this framework with slightly different labels and named it The Data Cycle, shown in Figure 2.3 (Gould et al., 2015).

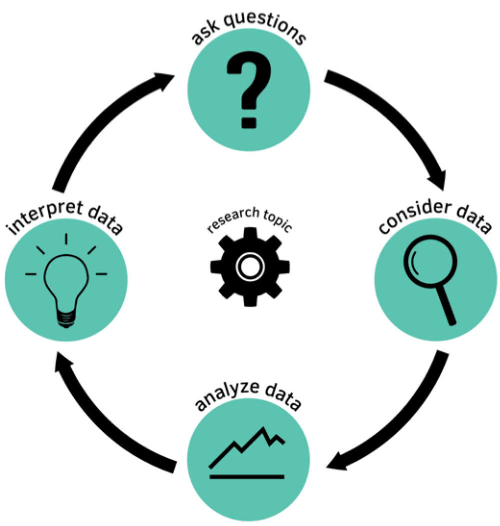

Figure 2.3: The Data Cycle. Reprinted with permission from 'Introduction to Data Science Curriculum v. 3.0,' by R. Gould, S. Moncada-Machado, T.A. Johnson, and J. Molyneux, 2015, p. 34.

Keeping in line with Wild and Pfannkuchs requirement for "statistical to contextual," the "research topic" at the center of the Data Cycle MUST be a real-world problem and be contextually relatable. The Ask Questions stage is the ideal place to begin in a statistical thinking process. In this phase, students ask statistical questions related to a real-world research topic. The Consider Data phase is slightly different than the GAISE Collect Data one by the inclusion of data that were previously collected. The last two parts of the cycle, Analyze Data and Interpret Data, agree with the methods of their respective GAISE framework components. It is important to note that although the Data Cycle appears to have a definitive starting place at asking questions, it is not necessary to begin there. As an example, in many classroom activities, data have been provided, so it might make more sense to begin at the Consider Data phase in these scenarios.

2.2.2 Observing Statistical Thinking with Model Eliciting Activities

One way to observe statistical thinking is to use Model Eliciting Activities (MEAs) to determine how participants navigate through a statistical investigative process. Model Eliciting Activities (MEAs) are designed to elicit participants' thought-processes while they engage in an open-ended problem-solving session (Lesh et al., 2000). In their paper, Lesh et al. introduce the characteristics and purposes of these activities through six key principles, summarized below:

1. **The Model Construction Principle:**
   The goal of any MEA should be "the development of an explicit construction, description, explanation, or justified prediction." (Lesh et al., 2000, p. 17)

2. **The Reality Principle:**
   MEAs should be meaningful and relevant to participants in order for them to "try to make sense of the situation based on extensions of their own personal knowledge and experiences." (Lesh et al., 2000, p. 25)

3. **Self-Assessment Principle:**
   Participants should be able to assess their progress during the MEA and their resulting solutions. (Lesh et al., 2000, p. 28)

4. **The Construct Documentation Principle:**
   MEAs should reveal the thought processes of the participants. In particular, is there

"an audit trail that can be examined to determine what kinds of systems" the participants were using and thinking about? (Lesh et al., 2000, p. 31)

5. **The Construct Shareability and Reusability Principle:**
   Solutions to an MEA should be able to be applied to other situations and usable by others. In other words, does the MEA "provide a way of thinking that is shareable, transportable, easily modifiable, and reusable?" (Lesh et al., 2000, p. 33)

6. **The Effective Prototype Principle:**
   MEAs are "most effective when they provide rich and memorable contexts for learning and for discussing important mathematical ideas." (Lesh et al., 2000, p. 34-35)

These MEA principles are directly in line with our definition of statistical thinking and the Data Cycle, so it follows that the use of an MEA will allow us to observe when participants are in, or are using, different phases of the Data Cycle.

2.3 Getting Stuck & Unstuck While Learning

Although little research has been done on getting students and/or teachers unstuck while learning, some relevant contributions are reviewed here. Bosch and Kersey offer a simple "5-Step Unstuck Procedure" that "empowers children with alternatives when they get stuck in their work and are unable to complete the work assigned to them" (1993). Although their research was geared toward younger children, it still provides some insights into ways to get students unstuck. The five steps are provided here (Bosch and Kersey, 1993, p. 229):

1. Reread the instructions.
2. Go on to the next problem or item, then go back and complete as much as you can.
3. Ask the peer assistant for help.
4. Place colored index-card-signal on desk for teacher to come.
5. Take out a book to read.

While Bosch and Kersey offer methods for younger children, McCartney et al. focused on students in higher education. They identified that "while learning new concepts and skills, students sometimes encounterobstacles that is, they get stuck and are unable to make progress toward learning and understanding" (McCartney et al., 2007). In their paper, they identified 35 basic strategies students used to get unstuck and learn. They grouped these into 12 broader categories and then furthermore into 4 super-categories, ultimately creating a hierarchy for the strategies (McCartney et al., 2007, p. 158). Figure 2.4 is a replication of their provided hierarchy.

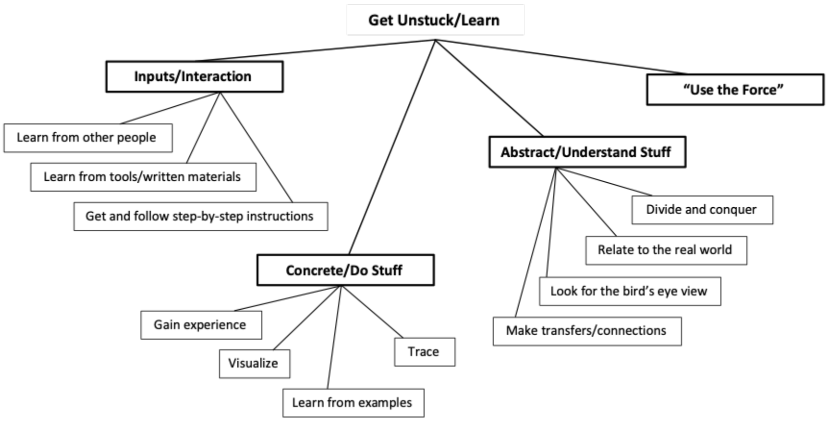

Figure 2.4: Hierarchy of Strategies for Getting Unstuck. Reproduced with permission from 'Successful Students' Strategies for Getting Unstuck,' by R. McCartney, A. Eckerdal, J.E. Mostrm, K. Sanders, and C. Zander, 2007, ITiCSE '07 Proceedings, p. 158. Copyright 2007 by ACM.

Our research will use this list of strategies to identify when our participants get stuck and unstuck. Refer to Section 4.3.2 for more on this.

2.4 Video Analysis

This section discusses some of the major contributions to foundational research in video analysis. Software packages that were utilized for this papers analyses of videos are introduced and compared.

2.4.1 Deductive Video Analysis

Much research has been done on the best practices and procedures for analyzing data from videos. This research focuses on a deductive method, which is where a top-down approach to reasoning is taken. Oxford Dictionaries English defines the word deductive as "reasoning from generals to particulars" (2018a). Additionally, Glanvill noted that "all knowledge of causes is deductive" (1661). Therefore, since we are interested in the causes of statistical thinking, deduction appears to be the best method to use for our video analyses.

One approach to using video as a primary data source comes from context analysis, which places an emphasis "on the simultaneous verbal and nonverbal conduct of all participants in an interactional event and the relations of mutual influence (simultaneously and across immediate next moments) among all the interactional participants" (Erickson, 2006). Since MEAs require small teams to work on solutions to problems, this approach seemed best for our purposes as participants worked together in groups of three. Therefore, both their dialogue and actions could be observed and analyzed.

Interestingly, Erickson explains that a video by itself is not data, but that "it is a resource for data construction, an information source containing potential data out of which actual data must be defined and searched for" (2006). Because of this, transcripts can (and should) be created in order to provide one set of analyzable data from videos. In Ochs' chapter on "Transcription as Theory" in the book *Developmental Pragmatics*, she describes common methods of transcription for both verbal and non-verbal behaviors, and goes on to say that "what is on a transcript will influence and constrain what generalizations emerge" (Ochs, 1979).

Along with transcripts, videos can also be coded according to certain schemes. These codes act as another form of data that can be used for the analysis of videos. Chi describes this as "verbal analysis," and introduces it as a methodology for quantifying the coding of the actual "*contents* of verbal utterances" (1997). In addition, she explains that in this type of analysis, "one tabulates, counts, and draws relations between the occurrences of different kinds of utterances to reduce the subjectiveness of qualitative coding" (Chi, 1997, p. 272).

For the purposes of our research, verbal analysis and corresponding codes were created to denote different phases of the Data Cycle as research participants completed an MEA, as well as whether or not the participants were stuck. See Section 4.2.2 for a complete listing of the coding structure created for this project.

2.4.2 Software Packages Used in Research

At the beginning of this research, Inqscribe (Version 2.2.3; Inquirium LLC, 2015) was used to transcribe video files and Vosaic, formerly known as Studiocode (Version 10; 2015), was used to code them. To streamline this process, the transcripts and video codes were recreated in MaxQDA (Version 2018.1; 2018) since it allows for video transcription and coding within the same program. The transcripts can also be exported as Excel files for convenient sharing and collaboration between researchers.

CHAPTER 3

Background

3.1 Participatory Sensing Data & the History of the Mobilize Project

This research focuses on a subset of the big data paradigm (see Section 2.1), one that collects non-traditional data through the use of a sensor. Oxford Dictionaries English defines a sensor as "a device which detects or measures a physical property and records, indicates, or otherwise responds to it" (2018b). Specifically, this research targets a personalized method of sensor sampling known as Participatory Sensing, or PS (Burke et al., 2006). Unlike a human, a sensor cannot choose when or what data it will collect; it simply follows a specific algorithm that has been previously programmed into it. In participatory sensing, humans take on the role of a sensor, and are thus a direct participant in the sampling and data collection process. They too follow a specific algorithm that tells them when to collect data based on the occurrence of a certain "trigger" event. As an example, human sensors might record data whenever the weather changes, when someone is ready for bed, or when a person goes to throw away a piece of trash. The data can be collected by individuals using personal mobile devices and web services. PS is a unique approach for connecting people to big data. It allows participants to personally connect with the data and therefore have a vested interest about possible insights or inferences that can be made from such data since the information is about where they live, work, and play.

PS prompted a group of researchers at the Center for Embedded Network Sensing (CENS) at UCLA to pursue using it for civic engagement and STEM education. The director of CENS, Deborah Estrin, spearheaded this team and became one of the original PIs of Mobilize. The Mobilize Project was a grant funded by National Science Foundation (NSF) from 2010 to 2018. It began in 2010 as a collaboration between UCLAs Department of Statistics, Graduate School of Education and Information Sciences, and Department of Computer Science, as well as the Los Angeles Unified School District (LAUSD). LAUSD is the second-largest school district in the United States, after the City School District of the City of New York, with more than 730,000 students and an annual budget of over $7.5 billion (LAUSD, 2016).

The main focus of Mobilize was to introduce both statistical thinking and computational thinking into secondary level math and science courses by incorporating participatory sensing into the curricula. Mobilize hoped to determine whether introducing participatory sensing into secondary school classrooms could increase students interest in STEM fields (Gould et al., 2018).

3.2 Development of the Introduction to Data Science (IDS) Course

After the implementation of the Mobilize curriculum units in Algebra and Biology, the Mobilize project team saw an urgent need for a stand-alone mathematics course structured around inquiry-based learning with Participatory Sensing. The team discovered that using PS in the short units for math and science courses was simply not enough time for students to actually do anything productive with their collected data. Thus, the idea of Introduction to Data Science (IDS) was born.

According to https://www.mobilizingcs.org/, the IDS curriculum “teaches students to reason with, and think critically about, data in all forms” (IDS, 2019). The curriculum is separated into four units aimed to introduce students to exploratory data analysis. The units are described below:

- Unit 1: Data (variables, graphs, numerical summaries)
- Unit 2: Comparing Distributions & Intro to Probability (measures of center & spread, probability & chance, normal curves)

- Unit 3: Data Collection Methods (experiments, observational studies, surveys, sensors, web data)
- Unit 4: Predictions & Modeling (linear models, classification trees, k-means cluster analysis)

The Mobilize team was able to get IDS credited as a "statistics" course, and therefore allow students to validate the Algebra II requirement for college admissions by taking this class instead. The success was a result of many things falling into place at the right time: The University of California Office of the President (UCOP) recognizing "statistics" as validating Algebra II (University of California Office of the President, 2019); California's 2010 adoption of the Common Core curriculum and its focus on process and problem solving (Warren and Murphy, 2014); and LAUSD's desire to increase computation in its curriculum (Szymanski, 2015).

IDS was first implemented during the 2014-2015 school year. Nine teachers were recruited for this pilot year based on their adoption and successful performance of the Mobilize Algebra I curriculum units during the prior academic year. More information about this particular group of teachers can be found in Section 4.1.

CHAPTER 4

Research Study: Teachers & the Data Cycle

As a reminder, this thesis aims to answer the following research questions:

1. To what extent are teachers able to negotiate a statistical investigative process?

2. When do teachers get stuck and unstuck while navigating through a statistical investigative process?

This is a follow-up study to the one presented in the Statistics Education Research Journal (SERJ) about the ability of teachers to reason with participatory sensing data (Gould et al., 2017).

4.1 Research Study Participants

With approval from UCLA's Institutional Review Board (IRB), we gave a Model Eliciting Activity (MEA) (see Section 2.2.2) to 9 secondary school math teachers who were piloting the Introduction to Data Science (IDS) curriculum (see Section 3.2) during the 2014-2015 school year. All participants are licensed and credentialed mathematics teachers in the Los Angeles Unified School District (LAUSD). LAUSD is the second-largest school district in the United States, and teaches approximately 650,000 students. Many students attending LAUSD schools are at the lower end of the social-economic spectrum during the 2014-2015 school year, nearly 80% of students qualified for free or reduced-price lunch, and roughly 25% of students were classified as English Language learners (California Department of Education, 2019). To provide a more detailed glimpse into our participating teachers' classes, Table 4.1 shows the distribution of ethnicities of their IDS students.

Ethnicity	Percent
Hispanic/Latino	90%
Black/African American	4%
White/Caucasian	2%
Pacific Islander	2%
Asian	1%
American Indian/Alaskan Native	1%

Table 4.1: Distribution of Ethnicities for all IDS students, 2014-2015

Four of the teachers reported having taught for 15+ years at the secondary mathematics level, and the other five had all taught between 6-10 years. Although two of the teachers had taught AP Statistics, all of the nine had very minimal to no experience in working with data. All teachers had successfully implemented the Mobilize Algebra I curriculum at some point in the two years prior to the IDS pilot year.

To prepare for the IDS course, the participating teachers attended two summer workshops (3-day intensives) as well as five one-day workshops that occurred throughout the school year. During the first year of implementation of IDS, these teachers were active in evaluating the curriculum and became collaborators in its revisions.

4.2 Research Study Methods

This section explains how the data were collected for the study, introduces the specific MEA given to the research participants, and describes the video coding structure applied to the transcripts. Examples of each video code are also provided.

4.2.1 How and When were Data Collected?

During one hour of the February 2015 professional development workshop, the nine teachers were separated into three groups of three, and were tasked with completing an MEA within the specified time frame of 45 minutes. The MEA created for this project was based on Mobilize's Trash Campaign, a participatory sensing project where participants collected data when they discarded a piece of trash. The Trash Campaign had been completed by high school biology students and their teachers in the Los Angeles area during the previous year. They recorded data on their mobile phones every time they threw a piece of trash away during a five-day period. The resulting data contained information about the type of trash, the use of any recycling or compost bins, photos of the items, and GPS coordinates. All but one of the nine teacher participants had experience with the Trash Campaign from its use in one professional development workshop the previous year.

The actual MEA asked the teachers to come up with two recommendations to reduce the use of regional landfills and to write a letter to Los Angeles County detailing their suggestions with supporting evidence from the PS data. The teachers were given a news article to provide context for the MEA titled "Trash city: Inside America's largest landfill site," which detailed the problems facing Los Angeles County's primary landfill (Gutierrez and Webster, 2012). The teacher participants were also provided with a link to the landfill's website (www.lacsd.org), as well as the actual data collected from the Mobilize Trash Campaign (16 variables with roughly 2700 observations). See Chapter 6 for the Appendix on the Landfill MEA and its corresponding assignment documents.

Each of the three groups were videotaped as they completed the activity and transcripts were created of their dialogue. The groups were provided the Landfill MEA handout and asked to record their results in the form of a letter. In the allotted time, teachers were allowed to work for roughly 45 minutes; however, this proved to be an insufficient amount of time for most of them to complete the activity fully. The teachers used their own computers during the activity and had access to RStudio as well as the Dashboard, a data visualization tool developed by Mobilize researchers to facilitate participatory sensing in secondary classrooms (Tangmunarunkit et al., 2015).

4.2.2 Video Coding Structure used in Research

As noted in Section 2.4.2, MAXQDA was used for the analysis of this research due to its ability to integrate video coding directly onto transcripts. Two sets of codes were created for the videos: one for phases of the Data Cycle, and one for when groups appeared to get stuck or unstuck during the activity. For full transcripts and inquiries related to the coding structure used in this research, please contact the author directly at terriannajohnson@gmail.com.

The transcript was used to attempt to identify the corresponding phase of the Data Cycle that the teachers were engaged with at any particular point in time. Each group was assessed by two of the original researchers, with the third acting as a judge for any discrepancies. In the original research paper, only two of the teacher groups were compared. This thesis expands to include the third group of teachers, which was coded by only one researcher due to time constraints. The second group of codes, which aimed to identify specific times when teachers were stuck and unstuck, was done by the same researcher.

To better identify what phase of the Data Cycle teachers were in during the activity, colors were assigned to them. Figure 4.1 provides the color classifications given to each phase. Note that Statistical Questions were given a darker pink color to help differentiate between regular questions and statistical ones.

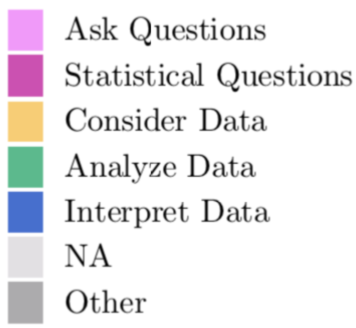

Figure 4.1: Data Cycle Color Classifications

Descriptions and examples of the video codes used to denote the phases of the data cycle are displayed in Table 4.2. The Data Cycle color classifications have been added for easier identification.

Ask Questions
Participant asks a question. *Example: "A public service announcement? Work problem? Work campaign?" "What else can we do?"*
Statistical Questions
Participant, more specifically, asks a statistical question. *Example: "So then do you want to do maybe, umm, if there's more trash produced by where they are. Like, umm, by location? Do we want to?"*
Consider Data
Participant discusses or references data of any kind. *Example: "That's a lot of data." "Two thousand six hundred thirty-two observations of sixteen variables."*
Analyze Data
Participant creates plots or tables and/or uses statistical analysis software. *Example: "We could, but I have to think about what type of variable we're looking at and then, that will let me know if I'm gonna do a histogram or a bar graph."*
Interpret Data
Participant provides interpretations of graphs and tables and/or uses outside knowledge to answer the research question. *Example: "So, like, it was...it was recyclable...given that it was recyclable, they put it in the recycle bin 54, you were pretty good. 54% of the time."*
NA
Researchers give instructions or warn about time. *Example: "Save yourselves, you have about fifteen minutes. Save yourselves five minutes or so to actually write it, like write maybe one suggestion down."*
Other
Off-task/irrelevant discussions or concerns about activity. *Example: "Can students do this?" "No. I don't think they're gonna do this type. It's just for us, right?"*

Table 4.2: Descriptions and Examples of Data Cycle Video Coding

By adding in the NA and Other categories into the coding scheme, every second of the teachers' progress during the MEA was able to be recorded and classified.

Descriptions and examples of the video codes used to denote the phases of "stuck" and “unstuck” are displayed in Table 4.3. X’s represent times where the teachers appeared to be stuck, while arrows represent times where teachers appeared to get unstuck.

Stuck XXXXXXXXXXXXXXXXXXXXXXXX
Group/participant is not able to continue the activity and needs help/clarification. *Example:* *“But remember there was a command, I forgot, where actually we want, we want the program to tell us exactly how many, so how many, umm I don't know, how many bottles are there. How many, like, categorize them. I forgot the command.”* *“Oh, categorize...yeah...”* *“Remember? It will just give you the numbers, not the graph. No, but it will give you the numbers, just the graph. I mean it won’t give you the graph, just the numbers...”*
Unstuck →→→→→→→→ →→→→→→→→→→→→→→→
Group/participant is able to find a solution to being stuck and continues the activity. *Example:* *“You have to do...you have to do capital ‘recycle.’”* *“I did.”* **all teachers look at their computers** *“Oh!” *laughs** **teacher fixes code in RStudio**

Table 4.3: Descriptions and Examples of Stuck/Unstuck Video Coding

4.3 Research Study Results

In this section, the two research questions are answered with the results from the study. Appropriate graphics, explanations, and interpretations are provided.

4.3.1 Teacher Use of the Data Cycle to Complete an MEA

Recall from Section 4.2.2 that video codes were created to indicate when teachers were in each phase of the data cycle during the MEA. Based on the ability to give and support at least ONE recommendation for reducing the use of landfills, the researchers determined that

Groups 1 and 3 were successful, whereas Group 2 was unsuccessful in completing the MEA.

One of the key MAXQDA features is the ability to create a “Document Portrait.” This function allows researchers to create a visual overview of all the codes for a particular video. The program calculates the total amount of video time and proportionally distributes each code to its relative frequency in chronological order. Because of this, it is relatively easy to compare codes between groups at similar times during the MEA. Each group’s document portrait depicting their progression through the Data Cycle will be individually introduced and discussed, followed by a comparison of all the groups.

To begin, we start with our first successful group, Group 1. Groups classified as “successful” were able to complete at least one recommendation for reducing the use of landfills, with appropriate analyses and interpretations from the provided data. Refer to Figure 4.2 for the discussion about Group 1’s movement through the Data Cycle phases during the MEA.

Figure 4.2: Group 1's Movement through Data Cycle during MEA

This group of teachers starts the activity by asking questions and considering data for the first few minutes. They are relatively quick to ask their first statistical question, which occurs at the 3 minute, 10 second mark. An important thing to note about statistical questions is that they do not always appear as an actual question, but sometimes as a suggestive statement. We see that here in the transcript for Group 1's first Statistical Question phase:

(3'10")	Michelle:	So then do you want to do maybe, umm...if there's more trash produced by where they are. Like, umm...by location? Do we want to?
(3'20")	Rosie:	We could do activity level.
(3'23")	Michelle:	Wait, what are the questions we're trying to ask I guess? We have to make plots based on that.
(3'26")	Rosie:	Well...it saysgive two suggestions, right? But I think there are things that we need to know. Like when is most trash produced?
(3'37")	Michelle:	Like when, what time, or where?
(3'39")	Rosie:	Like in what circumstances, so where, and what activity.
(3'43")	Michelle:	Uh-huh keep going.
(3'49")	Rosie:	And then, with the, the availability of recycling bins and trash bins in relationship with where.

Immediately afterwards, the teachers go straight into the Analyze Data phase using the provided Trash Campaign data. This is augmented by considering data and asking questions throughout. Their first data interpretation happens around 10'45". They continue to ask statistical questions and consider data afterwards and begin another cycle of analyzing. Once the second phase of analyzing is coming to an end (around the 18-minute mark), the teachers go back and forth between asking questions, considering data, and analyzing data to help them interpret their results. They spend the last 6 minutes of their allotted time writing up their recommendations using their interpretations of the data.

We see some interesting patterns come up in Group 1's movement through the Data Cycle. Notably, nearly all of the times they transitioned into the Analyze Data phase, they were immediately coming from asking statistical questions (4'15", 9'20", 15'20", and 20'25"). They also follow the Data Cycle pathway when interpreting data because they often go directly from analyzing data into the Interpret Data phase (10'45", 18'46", and 21'35").

These findings suggest that a rough adherence to the Data Cycle might be related to the success of this group. While we never see a strict pattern of transitions from Ask Questions to Consider Data to Analyze Data to Interpret Data, we do see Group 1 cycling through each phase at least once before the cycle started over. Rows 3-15 of the document portrait are portrayed in Figure 4.3 as an example of this.

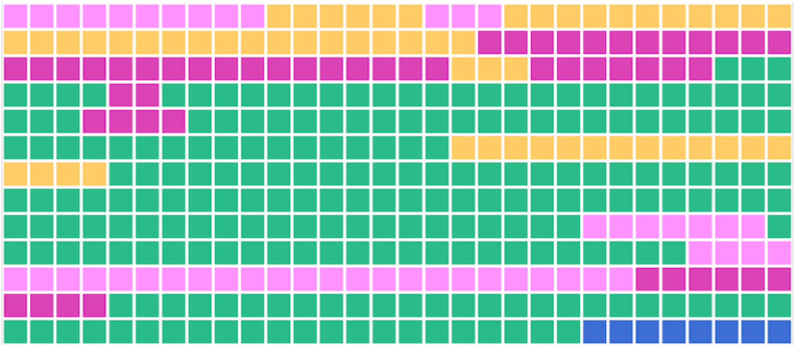

Figure 4.3: Group 1's Movement through Data Cycle during MEA (rows 3-15)

We see that the teachers go through the following phase changes (in order from top left to bottom right):

Questions →
Consider Data → Qs → **CD** → Qs → **CD** → Qs →
Analyze Data → Qs → **AD** → Qs → **AD** → CD → **AD** → Qs → **AD**→
Interpret Data

Note that Asking Questions and Statistical Questions are grouped together as "Questions" (denoted by Qs) in alignment with the original Data Cycle phases and Consider Data and Analyze Data have been abbreviated as CD and AD, respectively. Clearly, the group of teachers goes through each phase of the Data Cycle at least once on their way to a correct interpretation. In order for them to get from Consider Data to Analyze Data, they simply had to ask a few questions in between. Similarly, to get from Analyze Data to Interpret Data, they asked questions and considered data. Group 1 completed another full iteration of the Data Cycle later in the MEA as well.

Next, we examine Group 2's progression. Their movement through the Data Cycle during the MEA differs considerably from Group 1's. Recall that Group 2 was the only unsuccessful group in the research study since they were unable to produce any recommendations for reducing the use of landfills. Refer to Figure 4.4 for the discussion about Group 2's movement through the Data Cycle phases during the MEA.

Figure 4.4: Group 2's Movement through Data Cycle during MEA

Group 2 begins the activity by going straight to the Consider Data phase. They spend quite some time in Consider Data (roughly 3 full minutes) and proceed on to ask a few questions (none of which are statistical). However, they jump right to analyzing data at 4'10" and then try to interpret data just 18 seconds later at 4'28". The teachers go back and forth between their exploratory analysis and considering data before finally asking their first statistical question at 12'11", which is shown here in the transcript excerpt:

(12'11")	Vivian:	I think I would like to see uh...see how much they put in the trash that is recyclable and see what it is.

This sends them down a path of analyzing the data for roughly 9 minutes before they attempt their next major data interpretation. We see that they ask both regular and statistical questions throughout their analysis, but unfortunately, they are not able to make a correct interpretation. Perhaps this is because they rarely go from a question to analyzing data (the next phase in the Data Cycle). Specifically, there were six instances of the group going into the analysis phase without asking any type of question immediately preceding it (4'11", 8'55", 15'16", 18'04", 22'23", and 28'29").

In the full transcript, we find that Group 2 focused their analysis on an incorrect variable and were not able to gain any insightful interpretations from it. They chose to use the variable "whatTrash" (a text variable where the participants described their trash in their own words) instead of "type" (a categorical variable with only 3 options — recyclable, landfill, compost). Because of this, Group 2 was not able to come up with a supported recommendation by the end of the activity and we see this in the fact that their document portrait does not show a coherent structure of the Data Cycle. They attempt to interpret data in the last 3 minutes, but toggle between the other phases and cannot complete a recommendation.

Lastly, we look at the movement through the Data Cycle for Group 3, the other successful group in the study. Refer to Figure 4.5 for the discussion about Group 3's movement through the Data Cycle phases during the MEA.

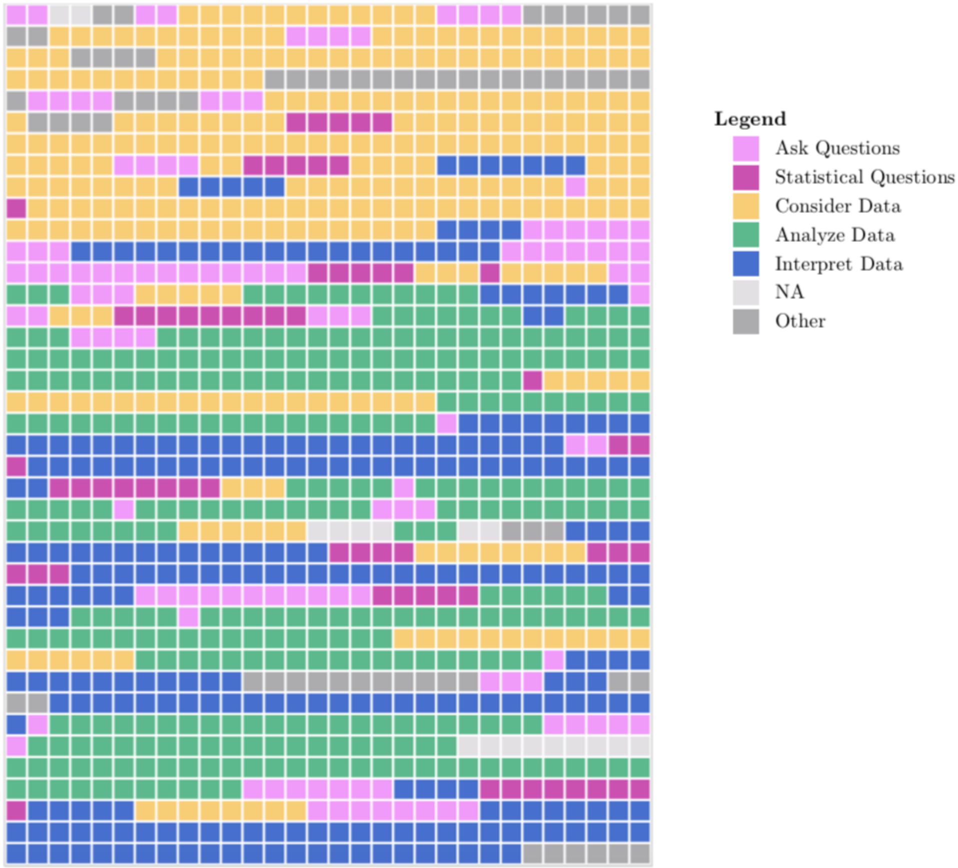

Figure 4.5: Group 3's Movement through Data Cycle during MEA

The teachers in Group 3 start with asking a question before transitioning to consider the Trash Campaign data. They ask a few questions while they explore the data and get to their first statistical question at the 6-minute mark, as shown in the transcript excerpt below:

(6'00")	Patty:	So, what do we do? Do we look at what people are doing?
(6'05")	Julie:	All right. So, what should we look...?
(6'06")	Patty:	Should we look at what people are doing?
(6'07")	Julie:	What variables do you think will help us?

Interestingly, this group starts interpreting data before any analysis has been completed at 8'22". As noted in Section 4.2.2, the Interpret Data phase can include outside knowledge used to answer the research question. This group used their own ideas about whether or not people are aware of what type of trash they are throwing away (landfill, recycling, or compost) to complete some interpretations. They continue to consider data and make interpretations before segueing into their first data analysis at 12’52”. The teachers look at data and ask questions to get them to a data-supported interpretation at 17’59”. Afterwards, the group goes through the Data Cycle roughly two more times before completing the task and providing a recommendation.

Similar to Group 1, Group 3 often went directly from asking questions (either regular or statistical) to the Analyze Data phase (12’53”, 14’09”, 14’46”, 20’34”, 21’07”, 21’31”, 25’41”, 26’19”, 31’04”, and 31’56”). They also traveled from Analyze Data to Interpret Data in succession a few times (13’30”, 14’24”, and 25’55”). We concluded that one feature that distinguished the successful groups from the unsuccessful one was their adherence to the sequence and order of the Data Cycle.

While it is necessary to discuss each group’s own advancement through the Data Cycle during the MEA, it is perhaps more interesting to compare their similarities and differences. All three document portraits mapping the progression through the Data Cycle for each group are laid side-by-side in Figure 4.6 to support this discussion.

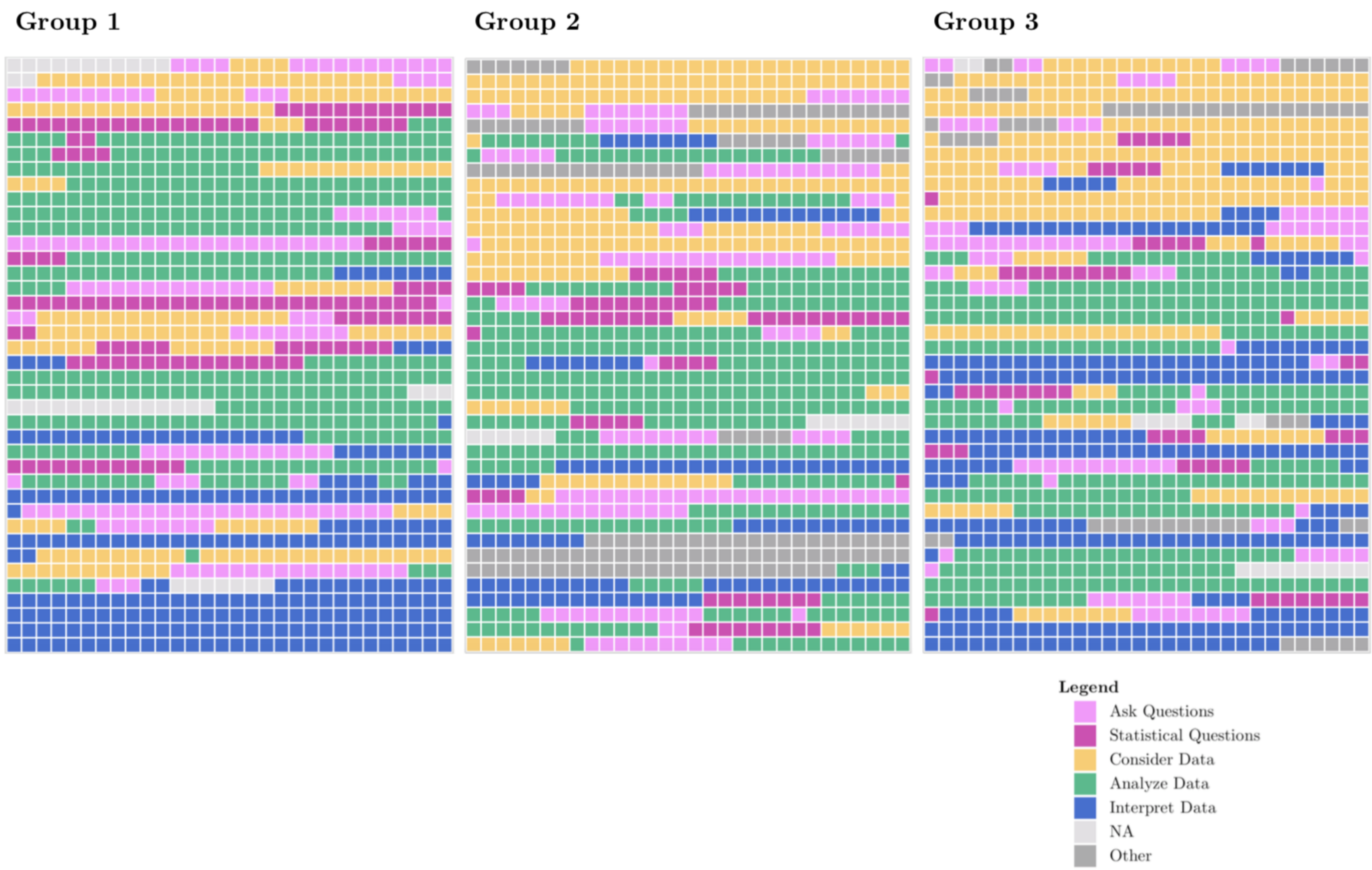

Figure 4.6: Movement through Data Cycle during MEA (all groups)

The thing that stands out most from the three groups is that Groups 1 and 3 both seem to cycle completely through the Data Cycle multiple times throughout the activity, while Group 2 never quite completes it even once. Instead, they jump from phase to phase with no clear order. Groups 1 and 3 also spend much more time on data interpretation than Group 2. Table 4.4 gives the percentage breakdowns of each group's time spent in the Data Cycle phases.

	Group 1	Group 2	Group 3
Ask Questions	13.9%	14.3%	9.6%
Statistical Questions	11.3%	6.4%	5.2%
Consider Data	16.2%	22.1%	26.2%
Analyze Data	34.0%	34.4%	28.4%
Interpret Data	21.5%	10.1%	23.8%
NA	3.1%	1.1%	1.4%
Other	0.0%	11.7%	5.4%

Table 4.4: Percent of Time Spent in Each Data Cycle Phase by Group

We can see that Group 1 spent significantly more of their time asking statistical questions than any other group. Group 3 spent more of their time in Consider Data and Interpret Data than the other groups, while Group 2 spent the most of their time analyzing data (albeit incorrectly). Interestingly, Group 2 spent a much smaller percentage of their time in Interpret Data than the 2 successful groups and much more time talking about things that were either irrelevant to the task or concerns about the activity in general.

Overall, it was concluded that Group 2's use of the Data Cycle was less helpful in allowing them to complete the statistical investigative process (i.e. the Landfill MEA) than Groups 1 and 3. Their lack of interpretations, as well as their sporadic transitions between phases of the Data Cycle contributed to them not being able to complete the assignment successfully. On the contrary, due to the successful completion of the MEA for Groups 1 and 3, the researchers determined that teachers are, in fact, able to negotiate a statistical investigative process, which answers the first research question proposed in this thesis.

4.3.2 Teacher Use of the Data Cycle to Get Unstuck During an MEA

As mentioned earlier, another set of video codes was created to determine when participants were stuck and unstuck during the MEA. Refer to Section 2.3 about what strategies the researchers looked for to identify moments when teachers were able to get unstuck.

For this portion of the thesis, the document portraits of each group's progression through the Data Cycle from Section 4.3.1 have been overlaid with whether or not the group was stuck. The updated graphics include the letter X to denote being stuck and a right-facing arrow to represent being unstuck.

We will first discuss the overall patterns of "stuckness" within and between each teacher group, as shown in Figure 4.7. Upon first glance, it becomes obvious that Group 2 was stuck much more than Groups 1 and 3. In other words, Group 2 had a lot more Xs on their document portrait compared to the two successful groups.

One general pattern that appears between the groups is that they were all stuck the most while in the Analyze Data phase of the Data Cycle, meaning this phase had the highest percentage of stuck events for each team. Logically, this makes sense because, during this phase, they should be creating plots and tables using statistical software (RStudio or the Mobilize Dashboard). Creating code for data analysis can prove challenging for experienced data scientists, so we would expect novice learners to struggle with this as well, and we see that in the document portraits.

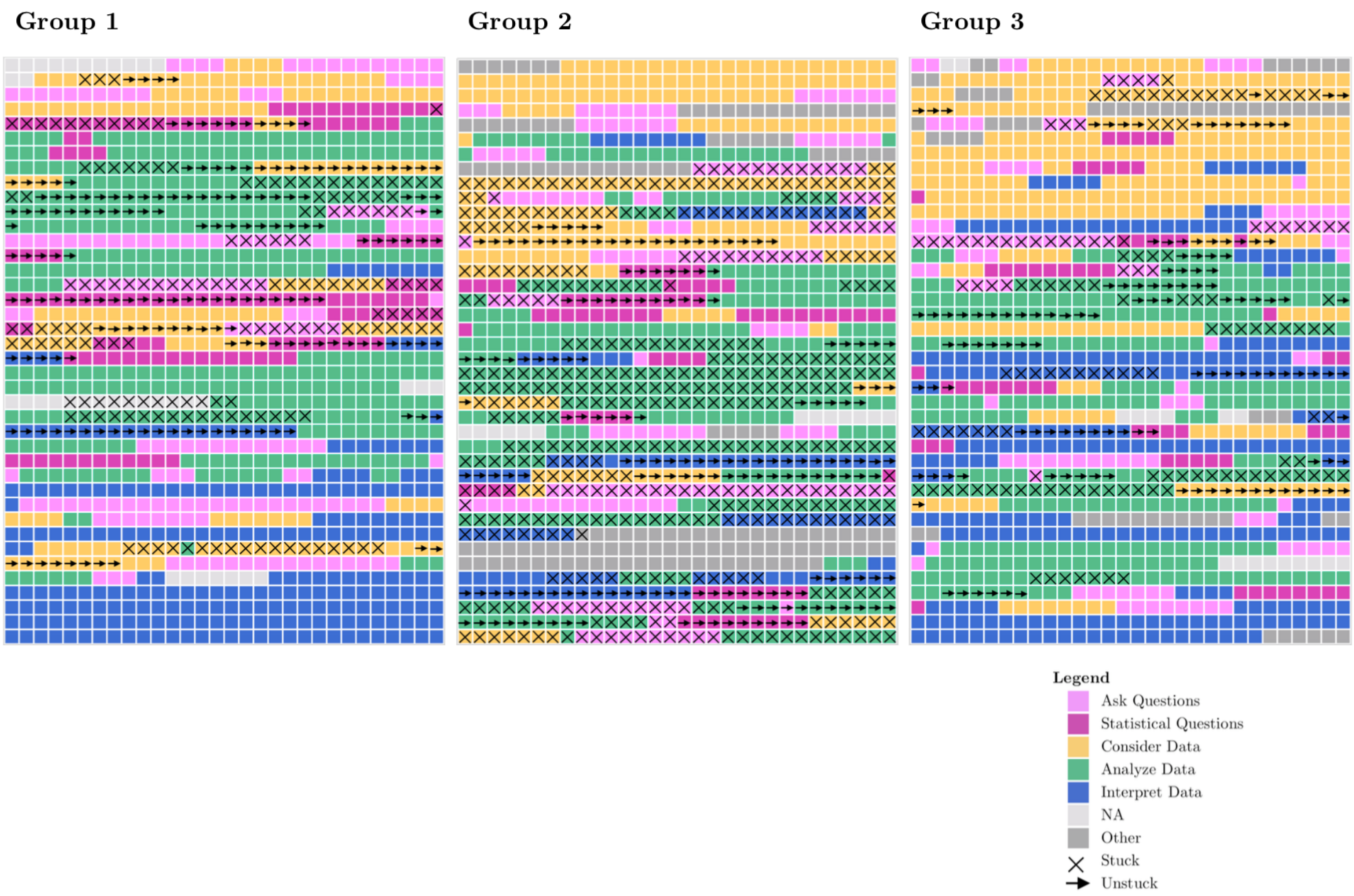

Figure 4.7: Movement through Data Cycle + Stuck/Unstuck (all groups)

For Groups 1 and 2, asking statistical questions seems to help in getting the teachers unstuck fairly often. Group 3 uses this strategy as well, but less frequently than the other two groups. A sample transcript from Group 1 using this strategy is below. Rosie and Ryan are in the Ask Questions phase while they are stuck, but then Michelle and Rosie pose statistical questions and the group becomes unstuck.

(13'20")	Rosie:	So we have to...	✖
(13'21")	Ryan:	What are the two things we would want to say?	✖
(13'23")	Michelle:	Well ok, number one if we increase the number of recycle bins...	→
(13'27")	Rosie:	Does the number of recycle bins, uhh, have a relationship with whether or not someone recycles? Is there a relationship between whether someone recycles or not?	→

One glaring difference about Group 2 is that they repeatedly were unable to resolve a phase of stuck-ness before becoming stuck again. This likely contributed to their group being unsuccessful in the MEA. We can also see that, for all groups, teachers do not always immediately transition from being stuck to unstuck. There is often a short period of time where they are neither stuck nor unstuck. One such passage from Group 1 is shown here as an example. We see that the group becomes stuck when trying to find a variable to indicate where a piece of trash was placed (13'41" to 14'09"). They then look at their given data and the provided handout (14'09" to 14'24") as references before finding the appropriate variable to answer their question, and therefore become unstuck (14'24" to 14'42").

(13‘41”)	Ryan:	How do you draw the, how do we, what do we have that measures that? Like, did they put it...Is there something that says they put it in the recycle bin?	✖
(13‘50”)	Rosie:	You know the...the data is just missing...like, is it recyclable? AND did you put it in the bin?	✖
(13’55”)	Ryan:	Did you throw it away? Did you put it in a recycling bin? We don’t know.	✖
(13’58”)	Rosie:	Yeah but it doesn’t...it doesn’t give you the information about whether or not it is recyclable. Because, what the question really is, “Is somebody putting something that is recyclable into the trashcan?”	✖
(14’09”)	Michelle:	So I see. What type of trash...Can we do something with what type of trash?...Let’s see what type of trash, and then...	
(14’21”)	Rosie:	Where they put it.	
(14’22”)	Michelle:	Where did you put it?	
(14’24”)	Michelle:	Oh look! They did. “Where did you put this trash when you were done?”	→
(14’26”)	Rosie:	So, this relationship between what type of trash, where did you put it, and then where were you, I guess.	→
(14’32”)	Ryan:	Oh they do ask them “where did you put it?”.	→
(14’34”)	Michelle:	3 categorical variables.	→

For a more in-depth comparison of the groups, Tables 4.5 and 4.6 were created. Table 4.5 depicts the percent of time each group was stuck and unstuck in each phase of the Data Cycle. The table has a column for each group and then lists the percent of time spent in each phase of the data cycle. These values come directly from Table 4.4. For example, in the Asking Questions phase, Group 1 spent 13.9% of their time there, compared to 14.3% for Group 2 and 9.6% for Group 3.

	Group 1		Group 2		Group 3	
Ask Questions		**13.9%**		**14.3%**		**9.6%**
	Given AQ,		Given AQ,		Given AQ,	
	% Stuck	*19.8%*	*% Stuck*	*50.3%*	*% Stuck*	*31.3%*
	% Unstuck	*1.2%*	*% Unstuck*	*0.6%*	*% Unstuck*	*0.0%*
	% Neither	*79.0%*	*% Neither*	*49.1%*	*% Neither*	*68.7%*
Statistical Questions		**11.3%**		**6.4%**		**5.2%**
	Given SQ,		Given SQ,		Given SQ,	
	% Stuck	*19.1%*	*% Stuck*	*7.8%*	*% Stuck*	*1.6%*
	% Unstuck	35.3%	*% Unstuck*	*49.4%*	*% Unstuck*	*11.3%*
	% Neither	45.6%	*% Neither*	*42.9%*	*% Neither*	*87.1%*
Consider Data		**16.2%**		**22.1%**		**26.2%**
	Given CD,		Given CD,		Given CD,	
	% Stuck	22.7%	*% Stuck*	*33.6%*	*% Stuck*	*6.1%*
	% Unstuck	23.7%	*% Unstuck*	*13.6%*	*% Unstuck*	*11.1%*
	% Neither	53.6%	*% Neither*	*52.8%*	*% Neither*	*82.8%*
Analyze Data		**34.0%**		**34.4%**		**28.4%**
	Given AD,		Given AD,		Given AD,	
	% Stuck	*12.5%*	*% Stuck*	*55.4%*	*% Stuck*	*19.1%*
	% Unstuck	*13.0%*	*% Unstuck*	*10.2%*	*% Unstuck*	*16.7%*
	% Neither	*74.5%*	*% Neither*	*34.4%*	*% Neither*	*64.2%*
Interpret Data		**21.5%**		**10.1%**		**23.8%**
	Given ID,		Given ID,		Given ID,	
	% Stuck	*0.0%*	*% Stuck*	*38.8%*	*% Stuck*	*7.0%*
	% Unstuck	*11.2%*	*% Unstuck*	*42.1%*	*% Unstuck*	*9.4%*
	% Neither	*88.8%*	*% Neither*	*19.0%*	*% Neither*	*83.6%*
NA		**3.1%**		**1.1%**		**1.4%**
	Given NA,		Given NA,		Given NA,	
	% Stuck	*27.0%*	*% Stuck*	*0.0%*	*% Stuck*	*0.0%*
	% Unstuck	*0.0%*	*% Unstuck*	*0.0%*	*% Unstuck*	*0.0%*
	% Neither	*73.0%*	*% Neither*	*100%*	*% Neither*	*100%*
Other		**0.0%**		**11.7%**		**5.4%**
	Given Other,		Given Other,		Given Other,	
	% Stuck	*0.0%*	*% Stuck*	*0.7%*	*% Stuck*	*0.0%*
	% Unstuck	*0.0%*	*% Unstuck*	*0.0%*	*% Unstuck*	*0.0%*
	% Neither	*0.0%*	*% Neither*	*99.3%*	*% Neither*	*100%*

Table 4.5: Percent of Time Stuck/Unstuck | Data Cycle Phase by Group

In addition to the relative frequencies given for each phase of the Data Cycle, conditional probabilities are provided to show how often each group was stuck, unstuck, or neither given a particular phase. As an example, given that Group 2 was in the Analyze Data phase, they were likely to be stuck 55.4% of the time. This means that a majority of the time that Group 2 spent trying to analyze data resulted in them becoming stuck and unable to progress through the MEA.

Another notable insight from Table 4.5 is the conditional probability of being unstuck given that a group was asking statistical questions. Group 1's data shows that they were able to use statistical questions 35.3% of the time to get unstuck. While Group 2 did not ask many statistical questions (6.4% of their time during the entire MEA), they got unstuck nearly half of the time when they did ask them.

Table 4.6 gives the reverse conditional probabilities of those in Table 4.5. Table 4.6 is perhaps more telling than the previous one in that it breaks down what phase of the Data Cycle each group was in depending on whether or not they were stuck. A particular observation of interest is the percent of time the groups were in the Analyze Data phase given that they were stuck. For Group 1, we see that if they were stuck, 31.1% of the time they were analyzing data. Group 2 and Group 3 also had higher percentages for this conditional probability (50.0% and 46.1% respectively).

	Group 1	Group 2	Group 3
Stuck	**13.7%**	**38.2%**	**11.8%**
Given STUCK,			
% Ask Questions	*20.1%*	*18.8%*	*25.5%*
% Stat Questions	*15.9%*	*1.3%*	*0.7%*
% Consider Data	*26.8%*	*19.4%*	*13.5%*
% Analyze Data	*31.1%*	*50.0%*	*46.1%*
% Interpret Data	*0.0%*	*10.3%*	*14.2%*
% NA	*6.1%*	*0.0%*	*0.0%*
% Other	*0.0%*	*0.2%*	*0.0%*
Unstuck	**14.8%**	**14.0%**	**10.5%**
Given UNSTUCK,			
% Ask Questions	*1.1%*	*0.6%*	*0.0%*
% Stat Questions	*27.0%*	*22.6%*	*5.6%*
% Consider Data	*25.8%*	*21.4%*	*27.8%*
% Analyze Data	*29.8%*	*25.0%*	*45.2%*
% Interpret Data	*16.3%*	*30.4%*	*21.4%*
% NA	*0.0%*	*0.0%*	*0.0%*
% Other	*0.0%*	*0.0%*	*0.0%*
Neither	**71.5%**	**47.8%**	**77.8%**
Given NEITHER,			
% Ask Questions	*15.4%*	*14.6%*	*8.5%*
% Stat Questions	*7.2%*	*5.7%*	*5.8%*
% Consider Data	*12.1%*	*24.4%*	*27.9%*
% Analyze Data	*35.4%*	*24.7%*	*23.5%*
% Interpret Data	*26.7%*	*4.0%*	*25.6%*
% NA	*3.1%*	*2.3%*	*1.8%*
% Other	*0.0%*	*24.2%*	*7.0%*

Table 4.6: Percent of Time in Data Cycle Phase | Stuck/Unstuck by Group

The values from these two tables can be used to guide teachers in how to get unstuck while performing an MEA and navigating through a statistical investigative process. For example, if a group is stuck, should they ask statistical questions in order to get unstuck? Or should they consider data? If we look at Group 2, we see that when they are asking statistical questions, they are unstuck 49.4% of the time. However, when they are considering data, they are only unstuck 13.6% of the time. A likely suggestion for this group would, therefore, be that they ask a statistical question when they become stuck.

One approach we considered to find insightful suggestions for teachers was looking at the transitions between when a group was stuck to when they became unstuck. In other words, will changing Data Cycle phases lead to a group getting unstuck? This question proved difficult to answer as our data were limited in their ability to provide causal relationships. The time increments (measured in fractions of a second) make it difficult to determine if groups get unstuck simply because they transition to a different phase.

Overall, the researchers were successful in determining when teachers get stuck and unstuck while navigating through a statistical investigative process. In general, the Analyze Data phase of the Data Cycle proves to be a common place for groups to get stuck, while asking statistical questions tend to lead groups to becoming unstuck.

CHAPTER 5

Conclusions & Future Work

The findings presented in this thesis provide evidence of successful answers to the original two research questions:

1. To what extent are teachers able to negotiate a statistical investigative process?

2. When do teachers get stuck and unstuck while navigating through a statistical investigative process?

Through the use of a model-eliciting activity, teachers showed an implicit ability to cycle in and out of different phases of the Data Cycle. We say implicit here because the teachers never verbalized which phase of the cycle they were in and never referred to it as an actual strategy they were using, but they seemed to engage in behavior that closely emulated the phases of the Data Cycle. By transitioning sequentially, two of the three teacher groups successfully completed the assigned MEA and were therefore able to negotiate a statistical investigative process.

Stuck-ness was also evaluated by overlaying stuck/unstuck video codes on codes classifying phases of the Data Cycle. It was determined that teachers typically get stuck while analyzing data and then use statistical questions to become unstuck. We believe that the trends found in our study lend themselves to possible suggestions for getting unstuck.

Recall that Bosch and Kersey created a 5-step approach to getting children unstuck (see Section 2.3) during classroom activities. Based on the findings from this research, we propose a similar 3-step guide to aid in getting participants unstuck when completing a statistical investigative process. Note that posing statistical questions and considering data, particularly with an understanding of the relationship between the data and the questions, is important in getting unstuck.

1. Generate possible statistical questions.
2. Check variables for appropriateness.
3. Look at the raw data.

In the future, this research can be expanded by analyzing how student groups progress through the Data Cycle while participating in a similar MEA. Document portraits of student groups could be compared to these teacher groups to determine if students navigate a statistical investigative process similarly or not, as well as if they get stuck in the same places or in the same phases.

CHAPTER 6

Appendix A: Landfill MEA

6.1 Landfill MEA News Article

Name:________________________________ Date:______________

Trash city: Inside America's largest landfill site (*excerpt*)

By Thelma Gutierrez, CNN and George Webster, for CNN

Updated 11:10 AM ET, Sat April 28, 2012 http://www.cnn.com/2012/04/26/us/la-trash-puente-landfill/

It's as tall as some of L.A.'s highest skyscrapers, but the only residents here are rats and cockroaches.

Welcome to the Puente Hills Landfill, the largest rubbish dump in America. Over 150 meters of garbage has risen from the ground since the area became a designated dumping site in 1957.

Now, six days a week, an army of 1,500 trucks delivers a heaving 12,000 tons of municipal solid waste from the homes and offices of L.A. County's millions of inhabitants.

"This used to be a dairy farm; a valley filled with cows producing milk. And now it's a geological feature made out of trash," said Edward Humes, author of "Garbology: Our Dirty Love Affair with Trash" -- a book that charts the history of garbage in America.

Humes says most of the waste arrives straight from the bins of local residents.

"If you're like most of us -- most Americans -- you're making seven pounds of trash a day. Across a lifetime that adds up to 102 tons of trash per person," he said.

In 2010 alone, Americans accumulated 250 million tons of garbage, and although recycling in the U.S. has increased by 34% since 1960, Humes believes the country's attitude to waste is still not sustainable.

"It's very convenient to roll your trash to the curb every week and have it disappear, but it's a magic trick -- and really there's not very much magic," he said. "We need to have less packaging; use less disposable items; (use) things that last longer; make purchasing decisions that are more studied and less wasteful."

The environmental impact of landfill sites varies depending on how well they're managed and resourced. However, typical problems include the contamination of soil and groundwater from toxic residues; the release of methane, a greenhouse gas produced during the decaying process that is more potent than carbon dioxide; and disease-carrying pests.

Tom Freyberg, chief editor of industry publication Waste Management World agrees with Humes that we should all be trying to reduce waste and increase the amount we recycle. However, he says it's likely there will always be a need for landfill, and we should applaud those sites that are well managed.

6.2 Landfill MEA Readiness Questions

Name:____________________________ Date:____________

Landfill Readiness Questions

Directions:

Answer the questions below and discuss your responses with your team members.

1. What types of items belong in a landfill? Give three examples of things you throw away that belong here.

2. The article implies that by recycling more, we can decrease the use of landfills. Why is this?

3. What types of items are recyclable? Give three examples of recyclable items that you use everyday.

4. How does an item that you throw away at school get to either the landfill or the recycling center? Why might items sometimes go to the wrong place?

6.3 Landfill MEA Handout & Data Description

Name:______________________________ Date:______________

Landfill Activity

Background:

The Los Angeles County Sanitation District (LACSD) would like to reduce their burden on the regional landfills, such as the Puente Hills landfill mentioned in the article. You can learn more about the LACSD by visiting www.lacsd.org and clicking on the "Solid Waste & Recycling" tab.

Because the LACSD knows that your class is familiar with participatory sensing campaigns and data, they are hoping you can help them explore the impact of landfills by using data from a city-wide participatory sensing campaign, titled the "Trash Campaign," that was conducted at a number of high schools in the Los Angeles Unified School District (LAUSD).

The task:

The LACSD is planning a public awareness campaign and wants to ask the public to take specific steps that will help reduce the landfill burden. Based on the data collected, they would like you to **make one or two recommendations** that would reduce the use of the regional landfills.

Specifically, they have asked your team to compose a letter in which you answer the following questions:

1. *What is/are the specific recommendation(s) you are proposing for the public awareness campaign?*
2. *Why do you think this will work? What evidence do you have to support this? Include any necessary plots and analyses.*

The data:

The survey questions/prompts for the Trash Campaign are provided below for your reference. The data can be found via the MobilizingCS public dashboard (https://lausd.mobilizingcs.org/#demo/) and can also be exported to RStudio.

Survey Question/Prompt	Variable Name	Data Type
1. Please take a photo of your trash.	photo	photo
2. Please describe your trash.	whatTrash	text
3. What type of trash? ❑ recyclable ❑ landfill ❑ compost	type	category
4. Where was this trash generated/found? ❑ home ❑ school ❑ work ❑ restaurants ❑ stores/malls ❑ in transit ❑ others	where	category
5. What activity generated this trash? ❑ eating/cooking ❑ drinking ❑ school work ❑ cleaning ❑ shopping ❑ I found it ❑ other	activity	category
6. Where did you put this trash when you were done? ❑ recyclable ❑ trash ❑ compost/green waste ❑ litter	receptacle	category
7. How many recycling bins can you see from your location?	howManyRecycle	number
8. How many trash/landfill bins can you see from your location?	numberTrashBins	number
9. How many compost/green waste bins can you see from your location?	numberCompostBins	number
AUTOMATIC	location	latitude, longitude
AUTOMATIC	timestamp	date, time

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