MAKING STATISTICS MATTER: SELF-DATA AS A POSSIBLE 
MEANS TO IMPROVE STATISTICS LEARNING 

by 

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ABSTRACT


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Research has demonstrated that well into their undergraduate and even graduate education, learners often struggle to understand basic statistical concepts, fail to see their relevance in their personal and professional lives, and often treat them as little more than mere mathematics exercises. This study explored ways help learners in an undergraduate learning context to treat statistical inquiry as mattering in a practical research context, by inviting them to ask questions about and analyze large, real, messy datasets that they have collected about their own personal lives (i.e., self-data). This study examined the conditions under which such an intervention might (and might not) successfully lead to a greater sense of the relevance of statistics to undergraduate learners.

(276 pages)
PUBLIC ABSTRACT

Making Statistics Matter: Using Self-data
to Improve Statistics Learning

Jeffrey L. Thayne

Research has demonstrated that well into their undergraduate and even graduate education, learners often struggle to understand basic statistical concepts, fail to see their relevance in their personal and professional lives, and often treat them as little more than mere mathematics exercises. Undergraduate learners often see statistical concepts as means to passing exams, completing required courses, and moving on with their degree, and not as instruments of inquiry that can illuminate their world in new and useful ways.

This study explored ways help learners in an undergraduate learning context to treat statistical inquiry as mattering in a practical research context, by inviting them to ask questions about and analyze large, real, messy datasets that they have collected about their own personal lives (i.e., self-data). This study examined the conditions under which such an intervention might (and might not) successfully lead to a greater sense of the relevance of statistics to undergraduate learners. The goal is to place learners in a context where their relationship with data analysis can more closely mimic that of disciplinary professionals than that of students with homework; that is, where they are illuminating something about their world that concerns them for reasons beyond the limited concerns of the classroom.

The study revealed five themes in the experiences of learners working with self-data that highlight contexts in which data-analysis can be made to matter to learners (and
how self-data can make that more likely): learners must be able to form expectations of the data, whether based on their own experiences or external benchmarks; the data should have variation to account for; the learners should treat the ups and downs of the data as more or less preferable in some way; the data should address or related to ongoing projects or concerns of the learner; and finally, learners should be able to investigate quantitative or qualitative covariates of their data. In addition, narrative analysis revealed that learners using self-data treated data analysis as more than a mere classroom exercise, but as exercises in inquiry and with an invested engagement that mimicked (in some ways) that of a disciplinary professional.
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Jeffrey Thayne
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CHAPTER I
INTRODUCTION

Over the course of my graduate education, I have taken a number of high-level statistics courses that included nearly every skill I would need to conduct research on a post-graduate level; nonetheless, many times, when I have had an opportunity to use those skills in a research context, I have had to re-learn them through self-study (e.g., referencing my old textbooks and seeking out online resources). Similar phenomena have been noted by many, particularly those in the situated learning movement: learning, they argue, often takes place best within a context of use. In this study, I will assume that statistical tools are deeply situated, with nuances and ambiguities that are understood best in a real-world context of inquiry.

Brown, Collins, and Duguid (1989) made this argument using language learning as an example. Learners cannot truly learn vocabulary words, they explained, using only self-contained dictionaries and a few textbook examples. They argued that language and vocabulary, involves “an unremitting confrontation with ambiguity, polysemy, nuance, metaphor, and so forth” that are invariably resolved only with “the extralinguistic help that the context of an utterance provides” (emphasis added, page 32). They used this example as a metaphor to highlight the ways in which other forms of knowledge are deeply situated — including, I would argue, statistics learning.

While this is only a broad-brush stroke caricature of the situated learning movement — a movement that has many different theorists and many different variations, and which I will discuss in more depth later — it nonetheless touches on what
I believe is an essential feature of effective statistics instruction: a relevant, immediately available context of application, wherein learners feel that they are taking part in an ongoing inquiry process in which statistics is being used as a tool for illuminating something new and important about their world. In contrast, too many learners complete statistics courses having only learned how to do new kinds of math problems (see, e.g., Pollatsek, et al. 1981; Strauss & Bichler, 1988; Mokros & Russell, 1995; Clement & Kaput, 1979).

Researchers have noted that many learners, while they understand that statistical inquiry might be useful during their future professional pursuits, often have little practical sense for how and when statistics is useful for them in the present (Kirk, 2002). This is at least in part because learners often are not engaged in life projects that require or make use of data inquiry or analysis (Cruise, et al., 1985; Roberts & Bilderback, 1980). Some have suggested that a solution to these challenges might lie in the use of student-collected data in statistics instruction (Aliaga, et al., 2005; Singer & Willett, 1990). More recently, others have proposed that that learners use of self-data, which refers to data collected by learners about themselves and their own activities, such as steps taken, heart rate, breathing rates, sleep patterns. The hope is that using self-data in statistics learning may connect statistical inquiry to more immediate concerns and interests of learners (e.g., Lyons, 2014), and by so doing, bring the revelatory nature of data inquiry out of the murky future of students’ yet-distant professional lives and into the concrete present of the here and now.
The use of self-data has been recently tested in an elementary school context in a series of design-based research studies (see, e.g., Lee & Drake, 2013; Lee & DuMont, 2010; Lee & Thomas, 2011), including some recent iterations that I have been involved in (see, e.g., Lee, et al., 2015; Lee, Drake, & Thayne, 2016). An argument has been made that the use of self-data offers a relevant, immediate context of application for statistics learners, and that self-data is inherently more meaningful to learners by virtue of the fact that it is about themselves (Lyons, 2014, Lee & Drake, 2013). This is significant for those who want to invite learners to see data analysis as instruments of inquiry instead of as mere classroom exercises — a goal that may be advanced by inviting learners to engage in data analyses that matter to them beyond the limited concerns of the classroom (Kirk, 2002).

In this study, I problematize and investigate the assumption that self-data is meaningful to learners simply by virtue of the fact that it is about the self. I explore the qualitative experiences of seven statistics learners — each of whom were taking an undergraduate statistics course, and had used self-data to practice statistics content over several weeks — to determine the conditions under which self-data analysis mattered to them. I discovered that each of their experiences were unique, and that self-data did not matter to any of them merely because it was about themselves; invariably, there were additional contributing factors required for the data to be meaningful to the participants.

To supplement this analysis, I explored the personal narratives of the participants, to see what mattered to them throughout their participation in the studied, and whether and how they expected statistics to play a role in their future lives. My hope was to
observe whether or not the use of self-data invited learners to engage with statistical practices as more than mere classroom exercises. In the process, I observed that the participants’ deep familiarity with their own data, coupled with their ongoing life projects and concerns, enabled some of the learners to approach the data with an invested engagement comparable in some respects to what we might expect to find amongst practitioners in a research context.

This study contributes to the broader research and projects of instructional technology by positioning technology as a tool for motivating learners — and more particularly, this study presents technology as a way of crafting a context in which learners step into data inquiry as more than a series classroom exercises, but as a meaningful tool for exploring their world. An important concern for researchers and designers of learning environments is developing ways to encourage sustained engagement among learners; this study explores how technology can be used to design instruction that leverages a situated learning perspective, and to (in some small ways, at least) shift the type of engagement that learners have with learning experiences.

In what follows, I will first articulate the problem statement, and explore some of the research that has been conducted related to the research questions of this study. Because the specific expressions used in my research questions are informed in part by my theoretical orientation, I will then identify and elaborate on the theoretical perspectives that inform this project. Following my theoretical orientation, I will identify the specific research questions addressed in this study, and then methodological approach I used to address them. Then, I will enumerate and the analysis and findings of the study.
In the conclusion section will discuss how the findings of this study may yield larger insights into how technology can be more broadly used as a way of making learning experiences matter to learners.

Problem Statement

Researchers have demonstrated that undergraduate learners struggle to understand many basic statistical concepts, including the concept of variability (Watson & Moritz, 2000), measures of central tendency (Bantanero, et al., 1994), probability (Garfield & Ahlgren, 1988; Konold, et al., 1993), and hypothesis tests (Haller & Krauss, 2002). Pollatsek, et al. (1981), for example, demonstrated that although most undergraduates understand how to compute a simple mean, they are unable to articulate what precisely the mean represents about the underlying data; they argue that while learners may gain a computational understanding of the mean, they often fail to understand the mean as a way of representing an underlying set of variable data. The same is true of a number of other statistics concepts and practices (Well, Pollatsek, & Boyce, 1990; Tversky & Kahneman, 1971; Wainer & Robinson, 2003).

In addition, undergraduate learners often struggle to see the relevance of statistical concepts in the practical activities of their anticipated personal and professional lives (see, e.g., Kirk, 2002). Researchers have discovered that undergraduate students tend to fear statistics and adopt a negative attitude towards the subject (Cruise, Cash, & Bolton, 1985; Onwuegbuzie, Da Rose, & Ryan, 1997; Tremblay, Gardner, & Heipel, 2000). This was noted early as Bending & Hughes (1954), who stated:
In faculty conversations concerning the teaching of psychology, the viewpoint is often expressed that instructors of courses in introductory statistics are faced with the special problem of the emotional attitude of the student toward the course. (p. 268)

In this light, Roberts and Bilderback (1980) noted that many undergraduate learners postpone taking introductory statistics courses as long as they can; they experience anxiety with regards to the subject that leads them to avoid it if and when possible (Bradstreet, 1996; Cruise, Cash, & Bolton, 1985). Similarly, Gal and Ginsburg (1994) make the claim that “statistics courses are viewed by most college students as an obstacle standing in the way of attaining their desired degree” (p. 2). Most students who take an introductory statistics course, researchers argue, “remember the pain but not the substance” (Peterson, 1991, p. 56) and put the content they learned “out of their minds forever” (Simon & Bruce, 1991, p. 22). As perhaps put most quite poignantly by Rosenthal (1992):

I appropriate the pejorative "sadistics" from student culture, to implore our community to acknowledge and legitimize students' perceptions of the quality of life in the course we create for them...[and] reflect the reality that unintended human suffering takes place under our watch. (p. 281)

Researchers have argued that one contributing factor in learners’ anxiety and negative attitude is learners’ perceptions of the worth of statistics — that is, the perceived usefulness and relevance of statistics to the learners (Cruise, et al., 1985; Roberts & Bilderback, 1980). Many learners are unsure of how statistical knowledge will advance
their particular disciplinary aspirations or how such knowledge will be useful to them in the practical affairs of life (Kirk, 2002). As such, their work in an introductory statistics course is often motivated by little more than to get a passing score in the course and complete the requirements of their major (Kirk, 2002). Other attitudinal factors have been identified, including learners’ level of interest in the subject and affective comportment towards statistics (Schau, 2003; Tempelaar, Schim van der Loeff, & Gijselaers, 2007).

Given that learners’ attitudes towards and anxiety related to statistics has been connected to their achievement in statistics courses (Chiesi & Primi, 2010; Murtonen & Lehtinen, 2003; Perepiczka, Chandler, & Becerra, 2011; Tremblay, Gardner, & Heipel, 2000), it may very well be that contextualizing statistical concepts in terms of how they might be used in the learner’s ongoing life activities — and demonstrating statistical concepts to be tools for more than merely completing academic requirements — may play an important role in facilitating learners’ understanding of statistical concepts. The fact that learners do not understand the contexts in which statistics is vitally useful, or how statistics plays a role in their personal and professional futures, may be more than just a sibling to the comprehension challenges that undergraduate statistics learners face in statistics courses; it may in part the source of those comprehension challenges.

In short, understanding not just the mechanics of statistical aggregations and inferences, but also developing the capacity to discern when and why such statistical concepts are relevant and useful is vital to becoming conscientious producers or consumers of scientific research (Garfield & Ben-Zvi, 2008). In part because of this, some researchers have argued that improving learners’ attitudes towards statistics is a
vital task for introductory statistics instructors, perhaps as vital as (and intrinsically
connected to) their task of facilitating a sound understanding of statistical concepts
(Garfield, et al., 2002). This may be why Gal & Ginsburg (1994) argue that statistics
instructors ought to do more than evaluate learners based on their competency in
completing exercises on their homework or exams; they ought to also assess learners on
their:

(1) interest or motivation for further learning,
(2) self-concept or confidence regarding statistical skills,
(3) willingness to think statistically in everyday situations, and
(4) appreciation for the relevance of statistics in their personal and vocational
lives (Section 2.1).

In short, according to Gal & Ginsburg (1994), adopting the ability to think like a
researcher, and to see the world in terms of questions that can be answered statistically, is
an important part of statistics learning. Indeed, Gal, Ginsburg, & Schau (1997) later
argued, “Teachers should aim to engender in students a positive view of statistics and an
appreciation for the potential uses of statistics in future personal and professional areas
relevant to each student” (p. 3). In other words, learners should be invited to care about
statistics, and the analyses they conduct as learners should matter to them.

In this light, I adopt as an assumption one of the implications of situated learning,
which is that understanding statistics as a valuable instrument of inquiry within a research
context may play a key role in understanding statistical concepts; that is, understanding
what statistics is for in a practical, situated sense may be crucial to understanding how to
engage in data analysis. I will explore some of these theoretical assumptions in more
detail shortly. For now, it can be assumed that it is a vitally important goal for statistics
instructors to help learners step into data analysis while trying to understand something
about their world that *matters* to them, as opposed to merely passing a test or completing
busywork.
CHAPTER II
LITERATURE AND THEORY

Literature Review

One concern of educators and researchers is the common practice of using simplified, contrived data sets in classroom instruction (see, for example, Greer, 2000; Singer & Willett, 1990; Snee, 1993; Hogg, 1991). While these datasets lead to simplified computational practice, they simply fail to interest, engage, or motivate students, and can lead to an over-focus on algorithmic understandings of important statistical concepts. Further, the practice of using contrived data may fundamentally misrepresent the core practices of statistics; Cobb and Moore (1997) explain, “Statistics requires a different kind of thinking [than mathematics], because data are not just numbers, they are numbers with a context” (p. 801).

Using contrived data can obscure that context and potentially turn statistics learning into a series of mathematics exercises—or, in other words, a series of exercises that have little import to the learner beyond meeting the requirements of the course (Kirk, 2002). Further, the practice of abstract computations using contrived data sets does not provide learners with a reason to care about the disciplinary practices that instructors are introducing to their students. Such data sets simply do not invite learners to step into a relationship with the data that is in any way comparable to the relationship that seasoned, professional researchers might have with their data.
The Use of Real Data

In response to these challenges (and others), some researchers have proposed that statistics learners use personally-relevant, self-collected data in the context of student-led data-inquiry, and have argued that that this may help learners deepen their understanding of statistical concepts (Aliaga, et al., 2005; Singer & Willett, 1990; Scheaffer, 2001; Lehrer & Romberg, 1996; Garfield & Ben-Zvi, 2008; Garfield & Ben-Zvi, 2009). For example, Singer and Willett (1990) recommend that teachers use in classroom instruction and practice datasets that:

1. Are authentic data taken from real measurements from a real-world sample,
2. Include background information about the demographics sampled, the instruments, and the purposes of the research,
3. Are of personal interest and relevance to the learners,
4. Afford the opportunity to learn something new (to the learners, at least),
5. Are amenable to multiple forms of data analysis, so that instructors can showcase and students can learn first-hand the advantages and disadvantages of various statistical measures,
6. Include raw data, rather than summary data, and
7. Include case identifiers, so that learners can potentially bring their own personal experience to bear in their analysis and interpretation of the results.

Singer and Willett (1990) are not alone in these recommendations: Scheaffer (2001) articulated as one of the guiding principles of his Quantitative Literacy Project
that “real data of interest and importance to the students should be used” (qtd. in Garfield & Ben-Zvi, 2008, p. 12).

Hancock, Kaput, and Goldsmith (1992) add to Singer and Willett’s (1990) recommendations, proposing that classroom learning in statistics education include not just learning about data analysis, but also about data creation. This recommendation was also presented (in the same year) by Cobb (1992) who argued that data production is an essential part of teaching introductory statistics. Moore (1998) argued that data collection and data exploration should be experienced firsthand by undergraduate students learning statistics. Cobb and Moore (1997) jointly argue that data production is an essential part of statistical inquiry, and that many of the misunderstandings of statistics learners can be traced to a lack of understanding of how research was designed and how data was collected.

In addition, Hancock, Kaput, and Goldsmith (1992) propose a kind of project or inquiry-based learning paradigm, in which students learn and practice statistics using data that they themselves have collected in an effort to answer a real question and generate new knowledge. They argue that central to statistical literacy is the ability to ask and answer questions not just about the statistical measures used, but the sources of the data, how it was collected, and potential sources of variability in the measurements, etc. The goal of statistics learners, researchers argue, should be more than just computational ability, but the ability to “use real data to solve real problems and to answer authentic questions” (Hancock, Kaput, & Goldsmith, 1992, p. 337).
In short, meaningful data analysis requires a familiarity with the data and the context in which it originates, as well as a familiarity with the broader research questions that drive the analysis. For this reason, real-world data that is collected by learners can make learning experiences more meaningful to learners, and motivate them in their learning (Diamond & Sztendur, 2002). According to Neumann, et al. (2013), “real-life data not only assists teachers in communicating how data is analyzed but also why it is analyzed” (p. 60, emphasis added). That is, the use of real data — and particularly data collected by learners, based on the recommendations by Moore (1998) and Hancock, Kaput, and Goldsmith (1992) — may not just provide learners with a better understanding of statistical concepts, it may offer learners more reasons to care about what they are learning.

**Modern technology and Self-data**

The practice of using simplified, contrived data sets is in many ways a relic of a time when classroom constraints (such as time and resources) prohibited the use of real-life, messy data sets (Singer & Willett, 1990). However, computers have made computation significantly easier for students and teachers, and have made it more feasible than ever before to use larger, messier sets of data in classroom instruction and practice. Further, technology has also opened new possible sources for data production that statistics instructors may take advantage of when teaching data inquiry and statistics. Such an approach, it is argued, will help situate statistical concepts by anchoring the learning activities in inquiries that are personally relevant and interesting to the learners (Garfield & Ben-Zvi, 2008).
For example, one proposed response to these recommendations is to use new technologies — such as wearable activity trackers — as sources of real data for statistics learners. Consumers have recently begun using a class of body-sensory technologies that regularly measure and summarize information about their physical health and activity (Lee, 2014; Rivera-Pelayo, et al., 2012). These technologies include scales, heart-rate monitors, sleep monitors, and pedometers that automatically sync with a computer or web application that summarizes and displays the information to the user (Swan, 2012).

Examples include the Fitbit or the Jawbone Up, and other similar devices (Rooksby, et al., 2014). One such device (relevant to this study) is the Fitbit Flex, which is a small device that uses micro-accelerometers to sense changes in the device’s acceleration, and extensive algorithms that detect when those changes are likely due to a person’s gait. This data is used estimate the number of steps that the wearer has taken, the number of floors the wearer has climbed, and (using information about the wearer’s height and weight) the number of calories the wearer has burned each day (Takacs, et al., 2014). Other Fitbit devices (such as the Fitbit Charge HR) also measure the individual’s heart rate, using a sensor that is continually pressed against the wrist of the wearer. Those who do not have access to specially designed fitness activity trackers often find that they can obtain similar functionality from smart phone apps that track their steps while their phone is in their pocket, using the smart phone’s existing orientation-detecting technologies.

These devices have helped to cultivate a movement referred to by some hobbyist communities as the Quantified Self, wherein participants will regularly tabulate
information about their lives and activities, with the goal being a better understanding of themselves and their lives, often for the purpose of motivating and measuring their progress towards personal goals (Lee, 2014; Swan, 2012). Other researchers refer to these practices as part of a broader research umbrella of personal informatics, which refers to practices whereby individuals collect and analyze information that is personally relevant, for the purposes of self-reflection and advancing self-knowledge (Li, Dey, & Forlizzi, 2010). Researchers have recently begun to model the processes whereby consumers collect, curate, analyze, and act upon data they have collected about themselves (Li, Dey, & Forlizzi, 2010).

Preliminary investigations have shown that those who participate in QS communities frequently engage in activities (such as reducing and summarizing data, comparing data sets, reasoning about different measures of central tendency, etc.) that are “valued disciplinary practices” that statistics instructors attempt to teach their students (Lee, 2014, p. 1036). Most importantly, the participants in the community engage in these valued disciplinary practices because they care about the information such practices reveal about the world and their physical activities, and not merely because they have been assigned the work by an instructor — that is, they are concernfully involved in the practices of data analysis in ways beyond those most often proffered by conventional classroom contexts.

Self-data in the Classroom

Researchers have hypothesized that it may be possible to enhance statistics instruction by inviting learners to measure aspects of their daily physical activity and
engage in statistical reasoning with regards to the resulting data (Lee & DuMont, 2010; Lee & Thomas, 2011; Lee & Drake, 2013; Sun, Rye, & Selmer, 2011). These sorts of technologies, they argue, can be considered and investigated as learning technologies (Lee & DuMont, 2010; Rivera-Pelayo, et al., 2012). That is, statistics instructors may be able to leverage these technologies as more than just fitness motivators, but as sources of data for learners to use in a statistics learning context.

Lee and DuMont (2010) explored this possibility with high school statistics learners by inviting students to wear physical activity trackers that collected data about their daily physical activities (such as heart rate, or the number of steps taken, etc.). The students then used that data to practice and learn about statistical measures. The study suggested that learners may be less inclined to settle on an answer that contradicted their expectations, and more inclined to thoroughly understand the measures of central tendency they were using to represent the data, because they had a vested interest in the implications the data had for themselves and their physical capabilities. Lee and Thomas (2011) performed a similar study with elementary school students, which suggested that students who used self-data may perform better “when asked to reason about situations with more complex data and actual problems” (Lee & Thomas, 2011, p. 18).

Significantly, such data inquiry activities would involve the kind of data-creation encouraged by Hancock, Kaput, and Goldsmith (1992), and the resulting data set is likely to meet every single criterion listed by Singer and Willett (1990): The data would (1) be authentic, (2) include information about the samples and instruments, (3) be personally relevant to the students, (4) afford genuine opportunities for new knowledge, (5)
amenable to multiple forms of analysis, (6) include raw data, and (7) would include case
identifiers familiar to the learner. Learners would be able to reason about trends and
outliers in the data based on their experiences, and compare their discoveries with their
recollections of the personal activities they were engaged in when the data was being
collected.

These previous investigations have explored whether and how wearable
technologies might advance statistics understanding, but have not thoroughly investigated
one of the reasons many feel that self-data might be so valuable: the innate motivating
interest learners may have in data about themselves. Such forms of self-data, it is
assumed, may provide personally relevant applications of abstract statistical ideas
because it inherently more interesting to learners (e.g., Lyons, 2015; Lee & Drake, 2013).
As recommend by Singer and Willett (1990), the resulting data would be both real,
relevant, and perhaps even of intrinsic interest to the learners; learners may have more
reasons to care about what statistical measures reveal about the data sets they are
analyzing. Lee (2014) argues that there may be “an inherently intimate relationship with
the data that are collected because they are about ‘the self’.” Li, Dey, and Forlizzi (2010)
write:

The importance of knowing oneself has been known since ancient times. Ancient
Greeks who pilgrimaged to the Temple of Apollo at Delphi to find answers were
greeted with the inscription “Gnothi seauton” or “Know thyself”. To this day,
people still strive to obtain self-knowledge. (p. 557)
Because of this, they argue, “We know that people want to get information about themselves to reflect on” (p. 557). This desire for self-knowledge is assumed to be innate; that is, inherent in each individual’s intrinsic concern for themselves and their own life and activities. Providing learners with data about the self, in short, is assumed to resolve the challenge of helping learners to care about the data. One of the central purposes of this study is to address whether or not this is actually the case, and if so, under what conditions.

Theoretical Orientation

In the previous sections, I identified one of the problems that this dissertation attempts to address: statistics learners in an undergraduate setting often do not see the relevance of statistics in their personal or profession lives, and so often do not care about what they are learning in the course (beyond the fact that it is required to complete their degree). In this section, I will use theoretical insights from situated learning (as described by Lave & Wenger, 1991) and learning as embodied familiarization (as described by Yanchar, Spackman, and Faulconer, 2013) to argue that the life projects of the learner, and the context in which they are using and practicing statistics, matters when it comes to helping learners to understand statistical inquiry.

Both of these perspectives can be brought to bear when exploring how self-data might invite learners to care about what they are learning — and more specifically, how using self-data in a statistics learning context can invite learners see statistical practices as instruments of inquiry rather than as mere classroom exercises. The hope, of course, is
that learners can come to see statistics as having an immediate relevance in their future personal and professional lives (as recommended by Gal, Ginsburg, & Schau, 1997), in a way that they might not when engaging in data analysis with contrived data, or data not about themselves.

**Situated Learning**

The most fundamental theme of situated learning is that learning and knowing cannot be divorced from context — the situation is not only of interest to learning researchers, but it is at least as interesting and important as the mental life of the learner (Rogoff & Lave, 1984; Lave & Wenger, 1991). Learning, from this perspective, is as much a social practice as it is a cognitive or mental one; what is learned cannot be separated from how it is learned (Brown, et al. 1989). Furthering these arguments, Lave and Wenger (1991) introduced the idea that learning involves the acculturation of the learner into a community of practice. As such, it is not just a process of learning new skills or performing new tasks; it involves a change in identity, “becoming a new person with respect to the possibilities” (Lave & Wenger, 1991, p. 53) afforded by one’s community of practice.

**Basic Assumptions.** Brown, et al. (1989) challenged the idea that knowledge can be reified as an object that can be transferred from one mind to another. In the conventional paradigm, according to Brown, et al. (1989), “The primary concern of schools often seems to be the transfer of this substance, which comprises abstract, decontextualized formal concepts,” where “the activity and context in which learning takes place are thus regarded as merely ancillary to learning—pedagogically useful, of
course, but fundamentally distinct and even neutral with respect to what is learned” (p. 32). This assumption, however, is wholly rejected by situated learning theorists.

Situated learning began, in this way, as a critique of classroom approaches that attempt to present or teach knowledge in a way that is divorced from the practical contexts in which it is used. Brown, et al. (1989) argued that “learning and cognition … are fundamentally situated,” that knowledge is deeply dependent on context for meaning (Brown, et al., 1989, p. 32), and that divorcing knowledge from its practical contexts can in turn sterilize it of meaning for learners. With regards to statistics learning, it can be argued that practicing statistics using contrived and simplified data sets, and in a classroom context, can do precisely this: provide learners with a context in which their only reason to care about the analyses is because of the strictures and expediencies of the school and classroom context.

**Learning in a Community of Practice.** Furthering these arguments, Lave and Wenger (1991) introduce the idea of learning as a process of enculturation into a community of practice, in which participants engage with shared practices with greater or lesser degrees of “peripherality.” Learning, from this perspective, is a process by which participants in a community of practice move from peripheral towards more full participation in within the community. As such, it is not just a process of learning new skills or performing new tasks; it involves a change in identity, “becoming a new person with respect to the possibilities” (Lave & Wenger, 1991, p. 53) afforded by one’s community of practice.
One could say, then, that in a situated learning perspective, the locus of learning is less in the content being learned (as if learning where the “transmission” or “acquisition” of content knowledge or even skills), and more on the constructed identities of the learners within the community of practice in which they participate (an idea that falls neatly within the “participation metaphor” of learning described by Sfard, 1998). The learner takes on a relation with respect to that community, and it is this relation — the social identities of the learners within the community of practice — that best accounts for variability in individual learning (Askew, et al., 2008).

Cobb and Bowers (1999) explain that both cognitive and situated approaches use position as a central metaphor, but employ the metaphor in vastly different ways: cognitive approaches use the metaphor of knowledge changing physical location (learning is knowledge being conveyed from the mind of teacher to the learner, etc.), whereas situated learning perspectives use the metaphor of a learners position with regards to the social context in which they reside (learning is a change in social standing with respect to the community of practice in which the learner participates). Thus, in situated perspectives, it is not knowledge or understanding that changes position, but rather the learners themselves — and learners are moving through a social topography rather than a physical one.

**Situated Learning and Statistics.** Some have argued that the idea of situated learning may account for why transfer is often not observed between school and non-school settings, or between one learning context and another (Greeno, et al., 1993). The community of practice within which a learner participates may have as its shared
practices something fundamentally different than the explicit goals of an instructor.

Watson and Winbourne (2008) explain,

> In classrooms … learning may be about becoming a fluent member of the class and this may have little to do with doing mathematics. Instead it might be more about learning how to survive teacher's questioning, or learning how to cope with the behaviour of the student sitting behind you, or learning how to look clever with minimal effort. (p. 5)

Learners may become quite expert in these shared practices, and take on comparable roles afforded by the community (such as “good student,” “smart student,” “good-at-math,” “know-it-all,” or conversely, “bad student,” “bad-at-math,” etc.). In this sense, learning has taken place, and is taking place, as students move towards more full participation in the shared practices of the classroom community, but they may not be participating at all in a community of shared mathematical practices (except in the most trivial sense). They become full participants in the shared practices of answering teacher questions or completing exams (an apprenticeship in public school participation, perhaps), but less so of engaging in data inquiry.

From conventional (e.g., cognitivist) perspectives, the two may seem indistinguishable; a learner demonstrates that they have adopted the right mental heuristics or schemas by providing the right answers in class or on the test. To a situated learning theorist, however, it may come as no surprise when the same learner is unable to engage in basic data inquiry in a professional context, or if the learner is unable to discern when news media are misusing or misrepresenting statistical concepts — practices that,
except in superficial ways, bear little resemblance to those shared by many classroom communities (such as taking tests and earning grades).

**Statistical practices as tools-in-context.** The most fundamental theme of the work of Brown, et al. (1989) is that learning and knowing cannot be divorced from context — the situation is not only of interest to learning researchers, but it is at least as interesting and important as the mental life of the learner. In addition, Brown, et al. (1989) argue that content knowledge and concepts should not be treated as isolated, “abstract, self-contained entities,” but rather as tools that we use as we engage in larger sociocultural practices (p. 33). As tools, the concepts we learn can broaden the horizon of possibilities that are open to us, just as a car, for example, might expand the number of places we can visit in a day, or a wrench can expand the possibilities open to a craftsman (more on this later).

However, these tools are fundamentally situated, for how to use these tools rightly is determined by a broader community of practice — that is, the specific sociocultural context in which the tool is used (Brown, et al., 1989). From this, Brown, et al. (1989) conclude that role the learner plays within his or her social context has a crucial role in the learning experience. When applied to statistics learning, these perspectives open the possibility that statistical practices such as “calculating a correlation coefficient” can take on radically different meanings to the learner, depending on the social context in which the practice is introduced.

For example, for a medical researcher, a correlation coefficient is a tool for discovering associations between lifestyles and diseases; his role as a researcher is what
makes a correlation coefficient one of many instruments for saving lives. In contrast, for a student in a classroom, the correlation coefficient is a tool for completing assignments, passing a course, and ultimately securing a degree; his role as a student is what makes a correlation coefficient an instrument for pleasing the teacher and earning grades. In both contexts, the correlation coefficient was a tool, but what it was a tool for is fundamentally different each case, because of the differing situated contexts in which they were employed. One of the assumptions of situated learning is that learners will understand the tools in fundamentally different ways as a result.

**Learning as Embodied Familiarization**

Because this study investigates the ways in which using self-data in statistics learning can support learners’ personal, concernful engagement with statistics, the particular interests of learners on an individual level — and more particularly, the way in which statistical practices are (or are not) disclosed to individual learners’ as personally relevant — are vital phenomena of interest. For this reason, the language and constructs of learning as embodied familiarization (such as the term *concernful involvement*), as described by Yanchar, Spackman, and Faulconer (2013), can dovetail the insights of situated learning and provide useful tools of analysis.

Learning as embodied familiarization extends the philosophical and theoretical projects of situated learning by emphasizing the situated nature of human learning, and draws on hermeneutic and phenomenological traditions to explicate such experiences. While situated learning focuses on the situated context of the learner (and how the learner is enculturated into a community of practice), learning as embodied familiarization places
some additional focus on the *individual experiences* of the learner as they undergo such processes. This perspective also creates space for analyzing a learner’s engagement with learning activities in the context of their broader life story, ongoing concerns and interests, etc., even when those concerns and interests long precede and extend far beyond the immediate communities of which the learner is a part.

In short, while learning as embodied familiarization assumes that the immediate community and situation of the learner is intrinsically important to understanding learning, this approach treats learning *phenomenologically*, as an individual experience of the learner that takes place against the backdrop not just of the near social context, but also of their existing and ongoing fears, concerns, cares, interests, as well as their interpretations of their past and projections of their future. For this reason, this approach introduces a narrative approach to understanding learning, as well as emphasizes *disclosure* as a test case for learning (Yanchar, 2015).

But most importantly for this study, learning as embodied familiarization treats *mattering* as a top-level phenomenon of interest, and is thus uniquely situated to provide a vocabulary for the kind of exploratory analysis conducted in this study. This is because, unlike conventional approaches that treat engagement as a form of sustained attention that can be measured in behavioral terms, learning as embodied familiarization adopts the construct of *concernful involvement* (more on this shortly) — something that can be differentiated qualitatively, by identifying what *matters* to the learner in their involvement in the practices at hand, the problems they are trying to solve, and how those
concerns and problems are situated not just with respect to their social context, but to their unfolding life story.

**Basic Assumptions.** Learning as embodied familiarization—like situated learning—must be understood as a theoretical response to cognitive theories of learning, which place emphasis on individual cognition and treats learning as an encoding of information in the mind. The person is conceptualized as participating in a host of culturally meaningful practices, acting as a whole (rather than as a mind within a body). This means that researchers adopting this approach will avoid treating learning as a consequence of mechanisms within the mind, and instead as a holistic activity of a *human-being-in-context*, something that *persons* do (not merely minds). This involves some different language and terminology as well.

This perspective assumes that the situations and contexts in which persons act are "encountered as mattering" to the participational agent, even when they are mundane or routine (Yanchar, 2011, p. 280). Yanchar (2015) explains, encounter the world with a “kind of care or existential concern with the affairs of living that provides a basis for action such as making judgments, taking positions, and engaging in cultural practices” (p. 9 of accepted manuscript). This is the origin of the term *concernful involvement* — the term *concern* refers not just to the “thoughtful consideration” one might have for another, but rather “to the general sense in which the projects, events, and relationships of life matter to agents” (Yanchar, Spackman, & Faulconer, p. 219). Yanchar (2015) draws from writings of Gelven (1989), arguing that from this perspective, “one does not proceed
from the analysis of ‘I think,’ … but rather from ‘I care’” (qtd. in Yanchar, 2015, p. 7 of accepted manuscript).

For this reason, learning as embodied familiarization assumes that the learner’s concernful involvement in social practices and the practical affairs of life “will be situated within a developing life storyline” (Yanchar, Spackman, & Faulconer, p. 219). Yanchar (2011) elaborates, “viewing human experience and action as narratively oriented calls one to see life’s meaningfulness as temporally arranged and, in that sense, oriented toward the meanings of the past as well as the possibilities of the future” (p. 282). Because we are beings that care, and because we are enmeshed in the social world, our behavior is best accounted for in terms of an unfolding story—stories we tell about ourselves and our actions that are explicit and tacit, spoken and unspoken. Mattering is not something that we can measure or discuss in isolation from the meanings of the past and our projections of the future.

**Familiarity and Unfamiliarity.** From within the perspective of learning as embodied familiarization, individuals regularly encounter unfamiliarity against a backdrop of familiarity. These two terms—familiarity and unfamiliarity—take on a somewhat different meaning in learning as embodied familiarization than they might from other perspectives. Unfamiliarity, from this perspective, is *not* understood as encountering something that does not register as already encoded within a person’s memory (although it might include something akin to that). Rather, the concept of unfamiliarity cannot be understood without reference to the individual’s comportment with respect to the world.
Learning as embodied familiarization borrows from Heideggerian thought the idea that there are two *ways-of-being* in relation to the world. We can use an example from Dreyfus (1991) to illustrate this:

We hand the blind man a cane and ask him to tell us what properties it has. After hefting and feeling it, he tells us that it is light, smooth, about three feet long, and so on; it is occurrent for him. But when the man starts to manipulate the cane, he loses his awareness of the cane itself; he is aware only of the curb (or whatever object the cane touches) or, if all is going well, he is not even aware of that, but of his freedom to walk, or perhaps only what he is talking about with his friend. (p. 65)

In this example, the blind man illustrates two modes of engaging with the world, different *comportments* that an individual can have with respect to their surroundings. The first can be roughly described by the term “unready-to-hand” (a term borrowed from Heidegger), which can be roughly compared to explicit or reflective action with regards to the cane. In this mode, the cane is disclosed to the blind man as an object with properties, something that can be broken, repaired, improved upon, discussed, and analyzed in the abstract, etc.

The second way of approaching the tool is one in which the blind man is hardly aware of the cane (qua object) at all, but is instead using the cane to extend his peripersonal space and transform his horizon or realm of possibilities (qua Husserl, cited by Nemirovsky, et al., 2011), and is perhaps termed “ready-to-hand” (another Heideggerian term). In this mode of engagement, “one is involved in everyday practical activity and the phenomenon is transparent” (Kezar, 2000, p. 388). The distinction between “unready-to-hand” and “ready-to-hand” is sometimes referred to as the distinction between *occurrent* and *available*. 
These two comportments, or *ways-of-being*, are found in every aspect of human life. A mechanic who is working on the steering of a car is treating the vehicle’s steering wheel and apparatus as *occurrent*, an object of explicit concern that is disclosed to him *as an object* upon which he is acting. In contrast, someone driving the vehicle would be treating the same objects as *available* — such a person does not treat the steering wheel as an object she is moving in a circle in order to exert an influence on the vehicle, rather, she is merely *turning left*.

Similarly, someone learning a new language might treat every sentence as an object of explicit concern, words that must be put together in specific order and arrangement, while someone more fluent might merely be *asking for lunch*. Someone visiting a distant relative and helping to prepare breakfast might need to find the eggs, locate a whisk, figure out the mechanics of the stove; whereas the same person at home in their familiar kitchen might be merely *making eggs*, with none of those intervening steps disclosing themselves as distinct activities of explicit concern. (Lave, 1997, uses this exact example to make a similar claim, arguing that performing even familiar tasks with interruptions to our familiar context can change our comportment with respect to that task, “with predictable performance difficulties,” p. 66.)

This latter example might illustrate the concept of *familiarity* — the person is quite literally “at home” in his kitchen, which is *available* but not *occurrent* to him. His surroundings can be *made* *occurrent* to him if someone had, in his absence, rearranged his drawers and cabinets; suddenly, locating the whisk becomes a distinct task of explicit concern, and he might begin to think abstractly about the layout of the kitchen and
possible locations at which the tools he needs may be hiding from him. This might be an example of an encounter with unfamiliarity, which are encounters that interrupt a person’s tacit engagement with the world in at least some respects.

**Embody Familiarization.** When understood this way, familiarity and unfamiliarity become far more than merely cognitive phenomena; they can be understood and treated *phenomenologically* as a holistic sense of “at-homeness” contrasted with its opposite, whatever term we wish to use. Learning, in this sense, can be thought of as what happens (or what *can* happen) within encounters with unfamiliarity, as individuals strive to restore a sense of “at-homeness” in their world. It might be said that one aim of a learner is to restore the tacitness of whatever process has been interrupted and made *occurent*; or to once again relate to the world *ready-to-hand*.

This is not to say that taking things “unready-to-hand” is always accompanied by a sense of “ill-at-ease,” or is always something that individuals are striving to avoid; the mechanic might be quite *at home* treating a steering wheel as occurent, an object of explicit concern upon which he is acting. However, the car’s driver and owner might *not* be, with the steering wheel becoming occurent only in moments of crisis or breakdown. A linguist might be quite at home studying words and sentences as objects of explicit concern, but a person learning a new language is striving to move past that to a way-of-being where the language is once again *ready-to-hand*, practically invisible amongst the daily projects of life. Both the mechanic and the linguist are “at home,” however, precisely because the tools, knowledge, and practices of their respective trades *are* ready-to-hand.
In this sense, it might also be said that learning—from the perspective of learning as embodied familiarization—includes the process of acculturation into a community of practice described by situated learning. From the perspective of learning as embodied familiarization, an individual standing at the periphery of a community of practice may be entering unfamiliar territory; the norms, tools, and practices of the community must be taken as explicit objects of concern. As he is acculturated into the community, the norms, tools, and practices of the community become less occurrent and more available. The individual’s comportment with respect to those norms, tools, and practices change as the community becomes home.

However, from the perspective of learning as embodied familiarization, learning can also describe the process of a solitary individual learning to ride a bike, and the habituation of processes such as pedaling and turning. Over time, the learner ceases to “move the pedals” or “turn the bar,” and is instead simply “riding to school.” Of course, learning to ride a bike does not take place in a social vacuum, and the learner’s situated participation in a broader social world (such as, for example, a community of bike-riding students) certainly ought to be part of the analysis—but the process of habituation can be analyzed and discussed as learning, without necessarily drawing into the analysis a discussion of those broader social circles.

In other words, learning as embodied familiarization holds that, as a person acting holistically in-the-world, a learner who encounters unfamiliarity (and by such encounter is interrupted in his or her tacit engagement with the world) may engage in practices that restore familiarity. The modes of exploration are many, and can include questioning,
observation, emulation, systematic inquiry, apprenticeship, trial and error, etc. Some modes of exploration (such as enculturation) require little in the way of explicit or reflective attention, while others (such as self-reflection or systematic inquiry) may involve the full attention of the agent. Learning, from this perspective, is “meaningful engagement that involves a change in embodied familiarity” (Yanchar, Spackman, & Faulconer, p. 219), or an adjustment to the learner’s “sense of dwelling,” a new “at-homeness” from which they involve themselves in the world.

**Mattering and disclosure.** Expanding the ideas of hermeneutic thought further, Yanchar, Spackman, and Faulconer (2013) argue that the manner in which a learner’s antecedent familiarity is brought to bear is deeply dependent on the learner’s concernful involvement with the world. To illustrate this, we can draw again from an analogy to biblical interpretation: many readers of the scriptures find that verses seem to change meaning as the circumstances of their lives—and, thus, what matters to them at any given moment—change. Scriptural passages that mean one thing to a rebellious teenager may take on entirely a new meaning for a new parent, and still yet an entirely different meaning for a bereaved spouse.

In other words, similar to the argument made by Nemirovsky, et al. (2011), Yanchar (2015) argues that the manner of learners’ concernful involvement within a social context can disclose the world to them in different ways; the way in which a phenomenon discloses itself to learners depends greatly on “the manner in which it is engaged by participational agents for particular purposes” (Yanchar, 2015). Yanchar (2015) continues:
That is, phenomena show up—they are disclosed or revealed—in a given setting based on the concernful involvement of participational agents, including their tacit familiarity, purposes, use of equipment, and so on. It might be said, in this respect, that participational agents disclose (or reveal) a world through their concernful involvement; or that the world shows up for agents based on what they are doing as part of their fully-embodied, largely tacit practical involvement in the world. …

For example, everyday activity discloses water as useful for drinking or washing; other activities disclose water in other ways, for example, as a hazard to be avoided, as having certain chemical properties, or as a symbol of life … Each reveals something true about water, but not at the same time, since each disclosure is based on a particular way of being involved with it, and thus each conceals as well as unconceals something about the phenomenon in question. (pp. 10-11 of accepted manuscript)

In short, participational agents are conceived not so much as “gatherers of information” or even “constructors of meaning” (a more constructivist framing), but are rather “world-disclosers,” and the manner in which the world is disclosed to the learner is rooted in the learner’s concernful involvement against a backdrop of their antecedent familiarity. One could say that the ongoing projects of life the learner is engaged in, including their ongoing concerns—or what matters to them—are integral part of the “antecedent familiarity” from which we investigate the world.
This extends to all forms of learning. Another example—borrowing from Nemirovsky, et al. (2011)—might be that of learning to wield an axe; the axe (and the process of learning to use it) might disclose itself entirely differently to someone who is preparing to defend his family from attack than it would to someone who is preparing for the oncoming winter. In this manner, the idea of concernful involvement (the central theme of participational agency) is brought to bear on the hermeneutic circle that is learning.

**Statistical practices as concernful involvement.** The subtle theoretical distinctions between situated learning and learning as embodied familiarization may be deeply important for the researchers who propose these different perspectives, but for the purposes of this study, they usefully converge towards the same conclusion: learning to compute correlation coefficient will be an entirely different experience for a dissertation student hoping for a statistically significant result, than it will for an undergraduate who does not care what the result is (as long as it is the same as what is on the answer key on the test). The learning process will be yet different for a medical researcher trying to save lives.

Not only will each of these learners attend to different aspects of the curriculum (e.g., what teacher has not had students attend only to those aspects of the curriculum that they expect to be on the test?), the kinds of experiences that interrupt their tacit engagement will be different. What constitutes an “interruption of dwelling” depends heavily on the practices the agent is engaged in and the way in which those practices matter to him. Further, how the learner responds to an interruption of dwelling may
depend greatly on the nature of the learner’s concernful involvement as well. A confused undergraduate statistics learner who just wants to pass a class and move on with his degree might, for example, review the equations for calculating a correlation coefficient in a textbook; a graduate student who wants to get a statistically significant result might engage in conversation with an advisor as well.

To summarize, concernful involvement means that practices and activities are also fundamentally motivated by passions, concerns, and interests of the learner-in-context; this is true whether or not the learner’s concerns or interests are explicit or articulated. For example, a learner may be deeply concerned with passing a course, and this concern might be reflected in his or her priorities, attitudes, and behaviors, even if the student finds himself quite bored with the course and distracted in his classroom activities (e.g., his attention may wander until moments in which certain responses are vital to receiving a passing grade). The social context and community in which he acts invites him to step into those concerns.

Discussion

In this study, I adopt a blend of some of the language and constructs of both of these perspectives because I argue that the why of learning (that is, learner’s goals and concerns that underlie their engagement with the learning activities) plays a consequential role in how and what they learn, and particularly how the practices they are learning disclose themselves to the learners. I argue that these goals and concerns can be stepped into as part of the social context of the learner — something that situated learning theorists have long argued, and which learning as peripheral participation is uniquely
suited to explicate. In addition, I argue also that these goals can concerns can also be part of the ongoing life narrative and projects of the learner, as well as individually experienced and not handed to them solely by their immediate learning context — and the phenomenological approach of learning as embodied familiarization is uniquely suited to help explore this possibility.

In some ways, this approach reflects the insights of Saxe (1992) and Saxe and Guberman (1998), argued that when part of a larger community or collective, learner’s activities are goal directed, towards accomplishing tasks or solving problems that are set before the group. Saxe (1992) observed that for children engaged in economic practices, “math was not an end in itself, but was instrumental to individuals for achieving larger profit-related goals” (Saxe, 1992, p. 220) — and that, while engage in such practices, children developed sophisticated, situation-based strategies for solving a range of mathematical problems. Drawing upon these observations, Saxe (1992) designed activities for learners in which mathematics would be “richly woven into play but that math learning was not an end in itself,” and in which children would be “involved in both generating mathematical problems as well as accomplishing them” (p. 220).

In a similar fashion, we might say that this study assumes that, when undertaken for the sake of pleasing a teacher, passing a test, or getting a grade, statistical activities are not seen as instruments of inquiry by learners (to the same degree as they might by researchers), but rather as math problems and classroom exercises — and that this contributes at least in part to the difficulties that learners face when learning statistics. But when those same practices are situated in such a way that they are instrumental to the
learners advancing broader inquiries into their world (that is, where statistics practices are “woven into” an activity, but not an end in themselves) statistical inquiry may be disclosed to learners as instruments of inquiry, rather than as mere math problems. This, however, would require the inquiry activities in question to engage learners beyond the confines of their classroom obligations (that is, the concerns imposed upon them by virtue of their participation in the classroom as a student trying to obtain a degree).

In short, the goal of a self-data intervention may be to provide a context in which learners can develop the same sort of investment in the results of their analyses that disciplinary professionals experience in the course of their research, so that statistical tools may disclose themselves to learners in a likewise comparable manner. I argue that it there may be two distinct ways that self-data might invite learners to care about data analysis: (1) by providing a context in which statistics can help learners advance already ongoing life projects and concerns, and (2) by providing new possibilities for concern to learners, by inviting them into a new and changed comportment with respect to familiar aspects of their lives (e.g., treating once familiar aspects present-at-hand rather than ready-to-hand). In both possibilities, learners may be concernfully involved in statistical practices in ways motivated by more than the parochial concerns of the student-in-classroom.
CHAPTER III
METHODS AND PROCEDURES

Hypotheses and Research Questions

As stated earlier, the project of this study is to explore whether the use of self-data collected by learners in an undergraduate introductory statistics course offers learners opportunities for engagement that connect with their concerns and is more meaningful and relevant to them. In short, the specific objective of the study is to determine whether some of theorized advantages of self-data (e.g., Singer & Willett, 1990) are actually realized when students engage in a data inquiry project using self-data. This particular study focuses less on how the intervention helps learners to understand the statistical concepts, and more on how the intervention increases opportunities for learners to care about what they are learning (although, as explained, I take as a theoretical assumption that the two are deeply connected).

My suspicions—well-founded by prior research—were that undergraduate learners see statistical concepts as means to passing exams, completing required courses, and moving on with their degree, and not as instruments of inquiry that can illuminate their world in new and useful ways; my hope was that using self-data in a statistics learning setting would help disclose statistical practices and concepts to learners as instruments of inquiry, mattering to learners as sources of information about themselves and their world. The goal is to place learners in a context where their relationship with data analysis can more closely mimic that of various disciplinary professionals (e.g.,
researchers, practitioners, etc. who use statistics in their work) than that of students with homework; that is, where they are illuminating something about their world that concerns them for reasons beyond the limited concerns of the classroom.

My central questions, therefore, relate to how the use of self-data connects the learning experiences to the concerns to the participants. The precise nature of this mattering (as related to the use of self-data)—what it looks like in context, how it is manifest in activity, etc.—is not precisely clear, which is why I have chosen to take a more qualitative, exploratory approach in this study. My first question is to establish what forms of concernful involvement are opened up to learners when exploring self-data; for example, are they concerned with the analyses for reasons beyond concerns typical of students (grades, pleasing the instructor or researcher, etc.)? What are the narratives of the learners as they undertake these analyses? What role does self-data and data analysis play in those narratives? Are they able to approach data analysis as researchers do (with the same sort of investment in the results)?

The second part of the study explores the conditions under which self-data matters to learners; I do not expect self-data to matter to all learners the same, or all forms of self-data to matter to learners equally. So I am interested in exploring what might account for some of the (anticipated) variation in the ways that self-data engages the interests and concerns of the learners. What are the differences in the data, and in the learners, that can account for these differences? And how might this inform how instructors use self-data in statistics learning?
Borrowing from the rhetoric of learning as embodied familiarization, this litany of exploratory questions can be formalized into two distinct research questions, which each inform the methods and analysis of this study:

1. What new possibilities for concernful involvement are disclosed to learners who collect and explore self-data when learning statistics?

2. Under what conditions do the use of self-data (and the questions asked about the data) matter to learners, and in what ways?

Methodology

To explore the phenomenon of interest, I needed to both implement the intervention and study the experiences of learners as they participated in the intervention. To do this, I recruited 10 participants who were enrolled in an undergraduate statistics course, and invited them to track at least two aspects of their personal lives (from a list of possibilities that I provided). I then met with each of them individually 3 separate times during the course, and during those meetings I invited them to explore the resulting data using modes of analysis they had learned in their course. To help get at the experiences of the learners, I also interviewed each participant before the course began, and after the final meeting.

The intervention, as implemented, was likely different in many important respects from how the intervention would look were it to be scaled and implemented on a course-wide basis (e.g., one-on-one meetings vs. in-class discussions)—however, I was less interested in testing or evaluating the effectiveness of the intervention (except to report
any practical insights I had along the way about implementing such an approach), and more interested in understanding the experiences of learners who use self-data, and how different forms of self-data connect with their going concerns and interests. For this reason, while I approached the implementation with care, it was not essential that it resemble in every respect how self-data would be used by an instructor.

**Case Study**

The study, as designed, is best conceptualized as a multiple-case study of the experiences of 7 individuals: Kristen, Sara, Greg, Britney, Peter, Christ, and Brian.¹ The subject of the case study is the way collecting and exploring self-data matters to individual learners, based on their prior experiences with data and their expectations of the future. In short, I have studied mattering in the specific context of the use of self-data in a statistics learning context. Following the case study approach of Yin (2003), the study’s propositions—that is, the hypotheses I am testing in these case studies—are that (1) the use of self-data leads data analysis to matters differently to different learners, and under different conditions, and (2) that for at least some learners, the use of self-data affords new possibilities for concernful involvement.

These propositions helped to define the unit of analysis of this multiple-case study, which includes each individual’s past experiences with data collection and analysis, their experiences with collecting and analyzing self-data during their study, their

¹ All included names are pseudonyms to protect the anonymity of participants.
broader academic and personal interests, and their expectations and plans for the future, all as expressed through their pre- and post-interviews and individual data exploration meetings. The criteria for interpreting the findings of the multiple-case study will involve comparisons and contrasts between different participants’ narratives, as well as between the themes drawn from their experiences in a cross-case synthesis (Yin, 2003).

**Insights from Design-based Research**

One could also argue that this study draws on some elements of *participant observation*, a term used by ethnographers to describe a research practice wherein the researcher does more than merely *describe or document* a phenomenon or culture she is observing, but also participates in that phenomenon or culture (Glesne, 2011). The researcher, in such cases, is both observer and participant, and documents not just the experiences of others, but also her own experiences (and her interactions with the group she is studying). This study is not an ethnography in any sense of the term, but there is a sense in which I—as the researcher—am engaging in the very practices that I am observing, and interacting *with* the subjects whose experiences I am trying to understand every step along the way. For example, the experiences that I am studying in this multiple-case study are not experiences that the learner would have without my direct intervention and involvement in their statistics learning; I am studying, in a sense, their experiences within a learning context that is the product of their interactions with me (the researcher)—I am both participant and researcher in the interactions I am studying.
In this way, while this study is not situated within design-based research tradition, it does borrow some approaches and assumptions from design-based research. Design-based research is a perspective in which research is treated as an iterative process in which instructional activities are designed and implemented by the researcher — who can either be the instructor or work in cooperation with an instructor — and then improved upon and re-implemented (Design-Based Research Collective, 2003; Edelson, 2002, Brown, 1992). This well-established and growing research practice is prompted by the practical necessities of studying teaching interventions in a learning context.

Within the literature of design-based research, practical questions about the design of instruction become relevant and legitimate focuses of inquiry. In a similar fashion, the intervention depicted in this study (the use of self-data in a statistics learning environment) was designed and implemented by the researcher, and practical considerations related to the successful implementation of the intervention were treated as legitimate questions of the study. As I exposed learners to data that they have collected about themselves (in the interviews and data exploration meetings), I took care to note potential ways such an intervention might be improved upon by future researchers and instructors.

**Qualitative Instrumentation**

While quantitative survey instruments have been designed to assess learner’s anxiety and attitudes towards statistics (Bending & Hughes, 1954; Gal & Ginsburg, 1994; Gal, Ginsburg, & Schau, 1997), Gal and Ginsburg (1997)—who have themselves designed such instruments—argue that such instruments provide (at best) an incomplete
picture of the attitudes and affective experiences of learners, and can be fraught both theoretical and methodological issues. They suggest that “statistics educators interested in a deeper understanding of how their students perceive statistics and statistics courses could opt for the use of structured interviews” (Gal & Ginsburg, 1997, par. 50).

Whatever alternatives are used, Gal and Ginsburg (1997) argue that it is “useful to break out of the mold of perceiving students' attitudes as lying across linear paths, and of ‘attitude change’ as moving students ‘higher’ or ‘lower’ along such paths, as is the case when five-point Likert scales are used” (para. 49). They continue:

To make the learning of statistics less frustrating, less fearful, and more effective, further attention by both statistics educators and researchers should be focused on beliefs, attitudes, and expectations students bring into statistics classrooms or develop during their educational experiences. (para. 54)

It is for these reasons that I adopted an interview-based approach in this study, in which I conceptualized learner’s attitudes towards statistics as part of their concernful involvement—or comportment towards their data, data analysis, and statistics. In this study, learner’s attitudes are not conceptualized on a linear scale from negative to positive, but rather in terms of how much data and data analysis matters to learners, and towards what ends they matter; part of this involves learner’s expectations of the future, and how learning statistics, and conducting data analyses, plays a role in their anticipated futures.
Narrative Inquiry

Because of the nature of the research questions and theoretical orientation of this study, this study draws upon elements from narrative inquiry (e.g., Gubrium & Holstein, 2009; Connelly & Clandinin, 1990; McAdams, 2001). Learning activities are conceptualized in this study as mattering to a learner when a learner perceives or believes that the future will unfold differently (in ways he or she does not wish) if he or she does not engage in the learning activities. In order to investigate whether the use of self-data has impacted the way in which the learning activities connect with the ongoing concerns of the learner, it is vital to situate the learning experience not just in terms of its social context, but also in terms of its context of the ongoing life-story of the learner.

To clarify, getting at and understanding the way that the learning activities matter to learners—and more particularly, how the use of self-data connects with that mattering—requires that we not only investigate the experiences of learners during the learning episode, but also explore the learners’ understanding of the past and anticipations of the future. Throughout this analysis, the study will adopt one of the central assumptions of narrative inquiry (in addition to some of its interviewing methods): the experiences of learners are most meaningfully and richly understood when taken within the context of an ongoing life narrative.

As such, it makes sense to draw from some of the analysis approaches of narrative inquiry, which—according to Richardson (1997)—assumes that “narrative is the primary way through which humans organize their experiences into temporally meaningful episodes” (p. 27). In narrative inquiry, rather than asking participants in the research to
summarize, generalize, or structure their responses, the researcher asks for the participants account of particular experiences and events, and attempts to transform "the interviewer-interviewee relationship into one of narrator and listener" (Chase, 2011, p. 423). The interviewer records those stories, and then performs a sort of hermeneutical exegesis on them, attempting to understand the narrative in terms of its context, its audience, and the ones telling the story (Connelly & Clandinin, 1990).

Drake (2006) provides a good example of the use of narrative inquiry and narrative analysis in this way to explore the effects of curriculum reform in the lives of mathematics teachers—in Drake’s (2006) study, teachers were interviewed to get at their “mathematics life stories” (drawing from McAdams, 1993), had their classroom teaching observed, and were then interviewed again. This study uses a similar approach, except that activities between the two interviews consist of three data-exploration meetings. Drake’s (2006) study centered on the life stories of the teachers—the high points and the low points in their “mathematics” life story (using an interview approach adapted from McAdams, 1993). In a similar fashion, I hope to use narrative analysis to explore the way in which the use of self-data influences the way leaners understand and care about learning statistics.

Participants

Recruiting

A sample of 10 students was recruited from three different sections of two undergraduate statistics courses at a university in the Intermountain West. One section (referred to here as Section A) was taught on campus, and two sections were taught
online (Section B, and Section C). The on-campus section, Section A, and one of the online sections, Section B, were the same course, but taught by two different instructors. The other online section, Section C, was a different (but comparable) introductory statistics course. Both online sections were taught by the same instructor. The difference between the two courses was merely one of emphasis: one was designed specifically for students going into STEM disciplines, and the other was not. As compensation for their participation in the study, participants were given a $20 Amazon gift card for each meeting, totaling $100 in monetary value by the end of the study. These cards were distributed after each meeting, to avoid the possibility of coerced continued participation.

Recruiting from the in-person and online sections took place a slightly differently: For the in-person sections, I emailed students about 2 weeks before the start of the term and invited them to participate in the study. In this email, I explained the compensation participants would receive, the other benefits of participations, and the time commitment that participation will require. (Participants in the study would spend a little over 5 hours participating in the study, including two 1-hour interviews, and three 1-hour data exploration meetings.) With the permission of the instructor, I also attended the in-person course on the first day of class, explained the study, and extended an invitation to participate, using a paper copy of the sign up form and QSIA, included in Appendix C. For the online sections, I simply sent the same email to students during the first week of the semester. A copy of the email is included in Appendix A.
Participants

A total of 10 students were initially recruited to participate in the study. Two of the participants withdrew from the course within the first few weeks of the study, and were thus not included in the results. One of the participants was removed from the study because of non-participation (he continually rescheduled appointments until it was too late to complete the study). Four of the remaining participants were male, and 3 of them were female, and they ranged in age from 21-29. All of the participants were upperclassmen, and claimed a variety majors, including ecology, economics, and exercise science, nutrition science, biochemistry, and mathematics and statistics.

Table 1
Name, Gender, Age, Major, and Section of Participants

<table>
<thead>
<tr>
<th>Name</th>
<th>Gender</th>
<th>Age</th>
<th>Major</th>
<th>Section</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kristen</td>
<td>F</td>
<td>20</td>
<td>Conservation and Restoration Ecology</td>
<td>Section A</td>
</tr>
<tr>
<td>Brian</td>
<td>M</td>
<td>23</td>
<td>Economics</td>
<td>Section B*</td>
</tr>
<tr>
<td>Greg</td>
<td>M</td>
<td>25</td>
<td>Exercise Science</td>
<td>Section C*</td>
</tr>
<tr>
<td>Peter</td>
<td>M</td>
<td>25</td>
<td>Nutrition Science</td>
<td>Section A</td>
</tr>
<tr>
<td>Chris</td>
<td>M</td>
<td>21</td>
<td>Biochemistry</td>
<td>Section A</td>
</tr>
<tr>
<td>Sara</td>
<td>F</td>
<td>21</td>
<td>Mathematics and Statistics</td>
<td>Section B*</td>
</tr>
<tr>
<td>Britney**</td>
<td>F</td>
<td>29</td>
<td>N/A</td>
<td>Section A</td>
</tr>
</tbody>
</table>

*Online section.

**Britney does not have a declared major, as she is taking the course for professional development purposes at the behest of her employer.
Six of the participants took the statistics course because it was a requirement for their major (or minor), and one participant was taking the course as part of a professional development effort encouraged by her employer (the university where she worked). None of them were taking the course as an elective. Table 1 includes information about each of the participants who completed the study, who were each assigned a pseudonym for use in this study. A more detailed profile of each participant is included in the Findings section.

Procedures

QSIA Survey

After participants agreed to participate in the study, I provided them a list of possibilities for Quantified Self data collection, and invited them to identify the level of interest they had in tracking the items on the list. This list included their computer usage, their phone usage, their weight, their blood pressure, their mood, their breathing rate, the number of flights of stairs they climb (in terms of relative elevation), their heart rate, the number of steps they walked, or their sleep patterns, and is detailed in Table 2. This questionnaire will be referred to as the Quantified Self Interest Assessment (QSIA), and its purpose was to ascertain what types of self-data might be most interesting to each participant in the study. The complete questionnaire is included in Appendix B (and C).

After participants responded to this questionnaire, and based on their responses, I assigned each participant at least two different types of self-data to collect during the semester. This depended on what forms of self-data they rated highest on their list, the devices available to both me and the participants, and in part on conversation with the
participants during the initial interview. My highest priority at this stage was that learners track the aspects of their life they were most interested in tracking, so I at times adjusted my choices based on the reactions of the participants during the initial interview.

Table 2
*Self-data Collection Options that Were Listed on the QSIA*

<table>
<thead>
<tr>
<th>Options</th>
<th>Instrument</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steps</td>
<td>Fitbit tracker (any model)</td>
</tr>
<tr>
<td>Stair flights</td>
<td>Fitbit tracker (any model)</td>
</tr>
<tr>
<td>Sleep Quality</td>
<td>Fitbit tracker (any model)</td>
</tr>
<tr>
<td>Heart rate</td>
<td>Fitbit tracker (Charge HR or Surge)</td>
</tr>
<tr>
<td>Blood Pressure</td>
<td>Withings blood pressure instrument</td>
</tr>
<tr>
<td>Mood</td>
<td>Mood Panda app</td>
</tr>
<tr>
<td>Weight</td>
<td>Withings scale</td>
</tr>
<tr>
<td>Breathing</td>
<td>Spire device</td>
</tr>
<tr>
<td>Phone usage</td>
<td>Instant app</td>
</tr>
<tr>
<td>Computer usage</td>
<td>RescueTime computer app</td>
</tr>
</tbody>
</table>

**Tracking Devices and Apps**

Each of the possibilities for tracking included on the QSIA could be tracked by one or more devices that I would make available to the participants. Steps, stair flights, and sleep patterns can be tracked using a Fitbit Flex, the same device used in previous studies that have explored the use of self-data in a statistics learning context (e.g., Lee, Drake, & Thayne, 2016; Lee, et al., 2015). This device uses micro-accelerometers to detect a person’s gait, and the Fitbit software would use algorithms to, based on that data, estimate the number of steps a person has walked (Rooksby, et al., 2014). The Fitbit also uses an altimeter to detect changes in relative elevation, as long as those changes are not

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50
insignificant (at least 10 feet, for example). The Fitbit can use this data to estimate the number of stair flights a person has climbed (cross-referencing the data with step data, for example, to ensure that the elevation gain was not achieved through an elevator).

Heart rate can be tracked using a Fitbit Charge HR, a device similar to the Fitbit Flex, but includes both a numerical display and a heart rate monitor in addition to existing features of the Fitbit Flex. The heart rate monitor takes continuous readings, and the Fitbit software makes heart rate data available to users on a minute-by-minute basis (with averages taken across each minute). Blood pressure can be monitored using a Withings blood pressure monitor, a device that works very similar to other blood pressure cuffs, except that the process of pressurizing the cuff is entirely automated. Weight can be monitored using a Withings smart scale, a scale that connects to the user’s personal device using Bluetooth in order to record readings. Breathing rates can be measured using a Spire device, a device that is worn on the belt or bra-strap, and which uses micro-accelerometers to detect the rate the motion associated with breathing. The Spire device and software using algorithms similar to those used by Fitbit devices to estimate when and how deeply a person is breathing.

Computer usage and phone usage can be tracked using a service called RescueTime, a productivity enhancing app designed to help individuals spend their time on digital devices more judiciously. The app downloads onto the user’s computer or personal device, and silently tracks the amount of time they spend using each application on the device. It syncs this usage data, which can be viewed using an online dashboard. For Apple smartphones, however, RescueTime was unavailable, and an app called
“Instant” was used instead — which had similar tracking features, and allowed you to compile daily usage totals into a .csv file. Mood can be tracked using a phone app called T1 Mood Tracker, which prompts users input their mood. Users can use one of several existing questionnaires, or create custom questionnaires, and can vary when and how often the app prompts them to respond and record their mood.

Each of these apps and devices automatically records data in a database that can be downloaded and viewed in third party programs, such as R, Excel, or other statistical software packages — this was one of the criteria for including tracking technology as part of this study. In addition, the Fitbit Flex, the Fitbit Charge HR, the Spire device, and RescueTime can be set up to track autonomously, without continued interaction of the user (so long as the user wears the device, in the case of the Fitbit or the Spire). However, the Withings blood pressure monitor, the Withings smart scale, and the T1 Mood Tracker app each require the active participation of the user to record measurements — they cannot be worn continuously, and thus the user must remember (or be prompted) to make measurements on a regular basis. Once measurements are made, however, they are automatically synced and saved in the database (as with the other devices).

Of these options, only the two types of Fitbit, RescueTime, and T1 Mood Tracker were selected by participants who completed the study. Other devices were selected by participants who did not complete their participation in the study. There was only one instance where a participant was not able to track one of her top choices. Two participants expressed interest in tracking their weight, but I only had one smart scale available. I therefore assigned the scale to only one of them. In this case, based on
convenience; one of the participants was an online student who was planning to commute for interviews, and shipping a Fitbit device was less risky and more feasible than shipping a scale. For example, the participant who was assigned the smart scale withdrew from the course 4 weeks into the semester.

![Devices](image1)

*Figure 1. Devices and apps available to participants.*

**Initial Interview**

All participants participated in a semi-structured, initial interview. These interviews took place during the first and second weeks of the semester (with one interview taking place the third, due to scheduling conflicts). The protocol for this interview is included at the end of the document. Because it is a semi-structured interview, the prepared questions were reordered and modified as each interview
unfolded, as needed to ensure that I maintained a friendly rapport with the participant, following the best practices of semi-structured interviewing outlined Glesne (2011) as well as Kvale and Brinkmann (2009). Further, questions were sometimes added to explore additional avenues of inquiry that unfold during the interview (but unforeseen by the initial protocol).

The protocol provided was inspired in part by the mathematics life-story interview protocol used by Drake (2006), which was itself adapted from McAdams (1993). The purpose of this interview was to contextualize participants’ involvement in the study as part of a broader life-story, which includes their lives as already given (facticity) and their projections of the future (futurity) (terms drawn from Heideggerian thought; Guignon, 2002). It is important to understand — as fully as possible — the reasons the participants are engaging in university work and learning statistics. In addition, the purpose of some of the questions in the interview was to get a narrative sense for how statistics figures into the participant’s life-story — that is, to get a sense for how statistics as a subject, and statistical concepts specifically, disclose themselves to the learners in the context of their ongoing participation in university work and their projections of the future. The questions were designed to elicit stories from the learners about their past experiences with statistics, as well as to invite them to imagine how statistics will (or will not) figure into their future.

These questions were important for getting at the concept of mattering described earlier: learning a subject matters to the learners if their projections of the future differ in non-trivial ways depending on their success in and attention to the learning activities (or
if they believe their past would have unfolded differently had they not succeeded in or attended to prior learning activities). While it is difficult to get at the tacit mattering of in-the-moment practical engagement with learning activities, the questions are designed to elicit from the learners explicit projections of the future, and how those projections are impacted by their statistics learning.

In this study, the situated contexts in which statistical tools were employed were at least two-fold: the classroom context of the undergraduate statistics course, and the research context of the dissertation study. To this end, during this interview, I asked learners to articulate their reasons for taking an undergraduate statistics course, as well as their reasons for participating in the study. Their concernful involvement in the study (in addition to their involvement in the statistics course)—that is, their reasons for participating, whether and why their participation mattered to them—were assumed from the outset to be relevant to the research questions and analysis.

During this interview, I also asked them to explain their preferences listed on the QSIA — why the ones they picked were the most interesting to them, and why the ones lower on the list are less interesting to them. I also invited them to start thinking of questions they would like to ask and answer about themselves and their activities using the data collected. In addition, I asked the participants about their general interests, hobbies, and activities, and how those played into their learning of statistics and the self-data tracking activities they expressed interest in. A protocol for the initial interview is included in Appendix D.
To reduce the possibility that my conversations with the participants do not “manufacture” mattering where it might not otherwise exist, I tried to leave plenty of room for participants to express a lack of interest in the activities, or a sense that they do not matter to them. I tried to ensure that all responses — even those that indicate a lack of mattering — were validated as legitimate and appropriate responses to the questions I asked. For example, at the beginning of each interview, I said something similar to the following: “To begin, I would like to make sure that you know that my purpose is not to evaluate you, your performance in the course, or your participation in the study — nothing you say here can invalidate your participation, or make your participation in the study less valuable to us. I’m not interested the ‘right’ answers, because there aren’t any — simply the true ones.” (This is similar to an approach suggested by Russ, Lee, & Sherin, 2012, who argue that preambles of this nature can help reduce the possibility that participants will answer based on their perceptions of the interests of the researchers.)

![Diagram](image)

*Figure 2. Outline of interaction with participants in the study.*
At times, if I sensed that they were at all offering me responses based on my reaction or what they thought I wanted to hear, I would remind them of this. For example, at one point in an interview with one participant, I said: “I just want to reiterate [that] I'm not evaluating you in any way. We're not looking for the right answers; we're looking for what's true for you. … We’re interested in how all this fits into your particular world, so there's no right or wrong answers to any of these questions.” This comment is representative of several similar sorts of comments that I made during the interviews.

**Individual Data Exploration Meetings**

Following the initial interviews, each participant met with me individually three times throughout the study. The schedule of these meetings depended greatly on which section of the course the participant was in (since one section was a 7-week course, and two sections were 14-week courses). Roughly speaking, however, participants met with me during the final four weeks of their course, regardless of the section they were in (the fourth meeting being the final interview). The pacing and timing of the meetings themselves were not important to the study, so long as they happened sometime shortly after relevant concepts were discussed in class. Adjustments were made based on the individual schedules of the participants, as well as the pacing of the course. For example, one participant (Sara) was unable to meet during the last week of the semester, so I met with her the week following. Also, I postponed some meetings with participants so that they would meet with me after relevant concepts had been discussed in class, when the instructor fell behind their posted schedule.
### Table 3

**Approximate Sequence of Events in the Study**

<table>
<thead>
<tr>
<th>Week 1</th>
<th>Section A</th>
<th>Section B, Section C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Initial Interviews</td>
<td></td>
</tr>
<tr>
<td>Week 2</td>
<td></td>
<td>Initial Interviews</td>
</tr>
<tr>
<td>Week 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 4</td>
<td>Data Exploration Meeting 1</td>
<td></td>
</tr>
<tr>
<td>Week 5</td>
<td>Data Exploration Meeting 2</td>
<td></td>
</tr>
<tr>
<td>Week 6</td>
<td>Data Exploration Meeting 3</td>
<td></td>
</tr>
<tr>
<td>Week 7</td>
<td>Final Interviews</td>
<td></td>
</tr>
<tr>
<td>Week 8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Week 11</td>
<td>Data Exploration Meeting 1</td>
<td></td>
</tr>
<tr>
<td>Week 12</td>
<td>Data Exploration Meeting 2</td>
<td></td>
</tr>
<tr>
<td>Week 13</td>
<td>Data Exploration Meeting 3</td>
<td></td>
</tr>
<tr>
<td>Week 14</td>
<td>Final Interviews</td>
<td></td>
</tr>
</tbody>
</table>

The primary purpose of these three meetings was to explore with the participants the data they collected about themselves, using concepts they were learning about in class. The point was not just that they collect data about themselves while also concurrently taking a statistics course, but to *explore* their data *using* the forms of analysis they were learning about in class. The hope is not just that learners care about themselves and their lives, but that they begin to see statistical analysis as an instrumental tool for helping to reveal aspects of their lives — that is, that *statistics* begins to matter, by virtue of the types of questions being asked by the learners, and the fact that those questions are deeply related to their everyday lives. Therefore, documenting which statistical concepts are found by students to be useful in exploring
their data is an essential part of this study. I hoped to observe how different statistical concepts could be brought to bear on the different types of self-data that learners collected, and the different sorts of questions they asked about the data.

The precise nature of each meeting depended greatly on the data collected by the participants, and the kinds of questions they expressed an interest in asking and answering about the data. For this reason, a consistent, precise protocol was difficult to develop, as each participant tracked different aspects of their lives. However, templates for these meetings are included in the appendices. These templates were followed as closely as possible, with adjustments based on the interests of the participants, and the specific questions they were interested in investigating using their data. During these meetings, participants explored their data using R or Excel, depending on the section of the course they were in, with some scaffolding from the researcher. R is a powerful coding language that can be used for data analysis that many introductory statistics instructors have used in their courses (see, e.g., Verzani, 2014; Dalgaard, 2008), and which participants in the in-person course learned to use. Excel was used by participants in the online sections included in the study.
While participants were encouraged throughout the study to generate questions of their own, this proved to be more difficult than expected. Many of the participants were far more content to let me generate questions for them than I wished they would be—for example, when asked what questions they might want to explore in future meetings, one participant simply replied, “I don’t know.” Some of the participants did generate questions of their own, but not all of their questions were answerable using the data available to them (for example, one participant—who did not track his mood—expressed interest in analyzing the relationship between his sleep and his mood). In addition, ensuring that the data was formatted properly for each anticipated analysis was far too time-consuming to do during the meetings, and so I made sure to complete this stage of the analysis prior to each meeting.

Further, I needed to make sure that I knew how to perform each analysis in R or Excel, so that the time spent in the data exploration meetings could be productive (and not burdened by troubleshooting issues). For these reasons, I ended up playing a much
larger role in generating questions about the data than I intended or hoped; before each meeting, I prepared a series of questions that I knew how to answer using the tools and data that were available, and ensured that the data was formatted appropriately for the analyses that would be required (similar to the structured approach used by the researchers in Lee & DuMont, 2010, in their investigation of the use of personal devices in statistics instruction in a high school setting).

This is not to say that the participants played no role in generating the questions that governed the analyses of their data. During each meeting, I asked participants what they wanted to learn from the data, and used their responses when generating materials for the following meeting. For example, during the second data exploration meeting, I asked Britney what questions she wanted to ask about her data during future data exploration meetings, and she replied: “I want to know if my heart rate is higher on days with more steps. … Also, sleep and steps. Do I get better sleep on days that I exercise more? Because I feel like I do” (second data exploration meeting, June 12, 2015, 01:07:30). Her response informed the questions that I prepared for subsequent meetings with her.

In addition, I was often able to adjust pre-prepared analyses to investigate further questions participants asked while performing their analyses. And, finally, on a number of occasions, participants asked some the questions I brought to the meetings, even before I indicated that I had prepared for them beforehand—Sarah, for example, provided few useful cues as to what analyses I should prepare for, so I prepared the data so that we
could correlate her sleep and her steps; at the beginning of the following meeting, before showing her my preparations, she expressed interest in conducting precisely this analysis.

Before each analysis, participants were invited to discuss what they expected the results of their analysis to show, and why. They then conducted the analysis using R or Excel. They then interpreted and discussed the results with me, how they compared against their expectations, and what they learned from the results, and whether the results of their analyses are useful to them or have bearing on their activities moving forward. Participants were prompted to ask follow-up questions they would like to ask and answer about their data. During a few of the meetings, for participants who were using R programming, I included a worksheet to help them with the analysis; the worksheet prompted them to input elements of R programming into R studio to complete the analysis. This is because it was unclear to what extent participants had mastered the syntax and structure of the programming language.

The three meetings involved three different themes, respectively, which roughly mapped onto the schedule of the statistics courses: measures of center and variability, hypothesis testing (t-test), and correlation.

**Meeting #1.** The first meeting focused on aspects of the data such as the daily or weekly mean and median, or standard deviation, etc., as well as visualizing the data in histograms and box plots. One purpose of this meeting was to allow participants to familiarize themselves with the data and the types of questions they could ask about the data. A template for this meeting is found in Appendix E. For students in Section A, R
was used to visualize the data. For students in Section B, Tableau was used as a visualization tool, in addition to Excel.

**Meeting #2.** The second meeting focused on hypothesis testing, using the t-test as a central example. We asked questions about their data that could be answered using significance tests — for example, “Do I walk more on the weekends or during weekdays?” or “Do I use the computer more on rainy days than sunny days?” We imagined their data as a sample, and pretended that we were drawing it randomly from a larger dataset about which we were trying to make inferences, such as their daily habits generally (as opposed to the previous few weeks). A template for this meeting is found in Appendix F.

**Meeting #3.** During the third data exploration meeting, we explored their data using correlation (as well as regression, for learners in Section A), discussing connections between various aspects of their daily activities, such as their heart rate and their physical activity, or their physical activity and their sleep patterns. For example, some participants asked, “Is the number of minutes I spend restless at night correlated with the number of steps I take during the day?” while others asked, “Is my computer usage correlated (inversely or otherwise) with my physical activities?”

During these meetings, I also asked participants about their learning experiences in the statistics course. These interviews were brief, but helped to elicit a continuing sense of whether and how the learning activities in the course mattered to the participants, and how that mattering may or may not have evolved over the course of the study. For example, I asked the participants to briefly summarize what they had learned
in the past week of instruction, and then to explain whether and how they foresaw using those concepts and practices in their future academic and personal endeavors. For example, I would ask, “Tell me a little bit about what you've been learning. What have you been learning in the class?” Then I would follow it with, “Do you feel like knowing this stuff is useful to you in your future personal or professional life?”

**Final Interview**

During the final interview, I asked the participants to help me understand the study from their point of view, by telling me the story of their participation from the beginning. The purpose of this stage of the final interview was to elicit from the participants a narrative description of their experiences with the study, and how those experiences unfolded across time. I also asked them to remind me again what motivated them to participate, and what they expected to have gained from the experience. The purpose of these questions was to revisit some of their initial motivations for participating, and to see if they have changed or if the participants understand them in the same way.

I also revisited many of the questions in the initial interview, to explore how the learner’s projections of the future may have changed since the first interview — to see if statistics plays an increased or different role in the learner’s horizon of possibilities. My hope was to get a sense for how (and if) statistical concepts disclosed themselves differently to the learners in the context of their ongoing participation in university work and their projections of the future, as a consequence of their participation in the study. In these questions, I treated the participants as characters in an unfolding story, and
attempted to understand the motivations and reasons they did what they did. These questions were again inspired in part by the interview protocol developed by Drake (2006) and McAdams (1993).

I also asked the learners about their experiences both collecting and analyzing the self-data. Prior to these interviews, I reviewed the recordings of each of the previous meetings, and noted what questions they asked and what conclusions they drew from their data. I then asked each participant specifically about whether and how those questions and analyses mattered to them. These specifically tailored interviews were prepared with the hopes that they will yield “thick” data (as described by Colson & Geertz, 1975 and Denzin, 1989; see Ponterotto, 2006) related to the concernful engagement of the learners in study — what they valued while participating in the study and learning statistics, and what role statistics will play in their academic, professional, and personal lives moving into the future. The protocol for this interview is found in Appendix G (since the protocols for each participant differed slightly, the protocol included includes the questions used when interviewing Sara).

Data Sources

Each of the initial and final interviews was recorded using a video camera and transcribed, as well as each of the data exploration meetings. The data exploration meetings were not transcribed in their entirety, as many aspects of each meeting dealt with technical issues and assistance (e.g., explaining the semantics of R, or demonstrating how to input a formula in Excel). However, the data exploration meetings were reviewed
and every instance of non-technical conversation was tagged for analysis and potential transcription. Many of these moments were then transcribed, if it was determined that they were fruitful for further coding and analysis (e.g., a moment in which I describe at length the nature of a t-test might not be transcribed, while a following moment where the participant discusses how a t-test might be useful in looking at his or her data would be transcribed). This sort of “selective” transcription is encouraged by Glesne (2011) as a way of reducing the time and costs of data analysis, and focusing the researcher’s attention on more fruitful segments of recorded interview data.

Further, screencasting software was used to record screencasts of the learner’s activities on the computer while using R (an approach described by Tang, et al., 2006). The screencasts were used to complement the recordings and transcriptions of the meetings, so that when necessary, I was able to observe what was happening on the screen during the transcribed conversations. This process enabled me to document the statistical analyses performed by the participants, and the numeric results they obtained from those analyses — information that was not conveyed using the audio data alone (since neither myself nor the participants would verbally rehearse the numeric results of the data analysis each time an analysis was conducted). By cross-referencing the recorded videos and the screencasts, I was also better able to interpret the gestures of the participants as they point at and discussed what was on the screen.
CHAPTER IV
ANALYSIS

My approach to data analysis consisted of three stages of coding: one involving the conditions under which data and data analysis can be made to matter to learners, one involving the process of exploring each participant’s personal narrative in relation to their participation in the study, and one involving further theoretical insights that are grounded in my theoretical orientation and hinted at in the data. These coding stages each contributed essential components to my overall analysis and discussion. Throughout this analysis, I drew from the best practices of qualitative analysis described by Glesne (2011), and from coding suggestions offered by Saldaña (2013) and others.

Reasons for Mattering

The first coding process I performed was to explore the conditions under which data and data analysis might be most likely to matter to learners (beyond the concerns that might be undertaken by a student vis-à-vis their grade or degree). During this stage, I looked specifically for moments when participants expressed interest in data or data analysis, and coded for reasons they gave as to why. I was less interested in whether or not they were engaged and interested, and more interested in why (that is, what concerns, what interests, what ongoing projects the data analysis “plugged into”). In addition, when they were not interested or engaged, I was interested in the reasons they gave for their disinterest.
This was a two-step process, involving both initial coding and axial coding. The process is similar to but distinct from approaches used in grounded coding using constant comparative (Glaser and Strauss, 1967) — unlike grounded coding, I am approaching the data from within a theoretical orientation, but like grounded coding, I am refining and developing constructs that do not currently exist in the literature. For example, the result of this “reasons for mattering” analysis is a set of themes that has not pervasively been identified, and which I developed based on a combination of initial and axial coding — making this process comparable to grounded coding (Strauss and Corbin, 1998), but I am also not approaching the data without any guiding theories whatsoever.

**Initial coding**

The initial coding stage of this process involved a much larger “net” than merely “reasons for mattering,” as it was my first pass through the data, and I wanted to familiarize myself with the contents of the interviews. In this way, I combed through the transcripts starting with a “blank slate,” and coded aspects of the data that were interesting or which seemed relevant in some way to my research questions. At first, this was a more arbitrary process of “tagging” interesting things that I found in the data. As I progressed through the data, I was able to standardize my coding a little bit more (e.g., “competition” and “comparison” were combined into one code, “competition”). This sort of standardization was conducted iteratively as I coded each interview, in order to prevent the proliferation of redundant and similar codes. I also made extensive coding memos as I encountered interesting aspects of the data, and to document my ongoing coding
activities. At the conclusion of the initial coding stage, I had 71 unique codes that I had applied to the data.

Many of these codes were not particularly useful during this stage of the analysis (reasons for mattering). For example, I coded instances in which participants discussed data collection in the context of a competition with others; I had a suspicion that competition might serve as a reason for being concernfully involved in the collection and analysis of self-data. This suspicion was not confirmed by my analysis; it would have been an interesting aspect of the data, if there had been more than two instances of it, and if those instances had been anything more than tangential to why the data mattered to the participants (in one instance, for example, the Greg simply mentioned as an aside that he often compares his steps with his dad when they go hiking, but this did not factor into why data collection or analysis did or did not matter to him over the course of the study).

I also coded any and all instances in which participants discussed an extracurricular hobby or passion — something that I figured might be interesting as I began the analysis, and which was somewhat useful when familiarizing myself with the participants and their interests — but this code did not shed any light in the conditions under which data analysis mattered to the learners, since for most of the learners, the data collection and analyses were not conducted or even discussed within the context of those hobbies and passions.

However, other codes were useful to the analysis — they began to hint at larger themes and constructs that could help me understand when data analysis mattered to the participants (and when it did not). I specifically focused on moments where data or data
analysis did or did not seem to matter to the participants, and the reasons they gave as to why. I made an assumption that the conditions under which data or data analysis do not matter reveals something about the conditions under which they do matter. The following example illustrates this coding process for a passage in the transcript in which interest and mattering was explicitly discussed by the participant (in this case, Greg):

```plaintext
Jeff: So why was heart rate not as interesting to you as you thought?
Greg: I guess because I didn't see that it fluctuated, so there wasn't really anything, to me, that correlated as much with it, and so I was taking more steps, but my heart rate still stayed the same, or things like that. So it just didn't strike me as interesting enough to follow it I guess.
Jeff: Ok. And why was sleep interesting to you? Like why did that end up becoming...
Greg: I don't know; I guess it's just interesting to see different sleep patterns.
(Final interview, August 21, 2016, 00:06:48)
```

In the above passage, Greg had previously listed what aspects of the data collection and analysis he found to be interesting and engaging, and had listed sleep as interesting, and heart rate as less so. I prompted him to explain why, and he indicated (in line 2 of the passage above) that the lack of fluctuation — or variation — in his heart rate made it less interesting to him, in part because it meant that little that he did (such as physical activity) made a difference in the results. The first part of Greg’s response was coded (during the initial coding stage) as “Variability (reason for mattering)”, and the second part was coded as “Ability to influence (reason for mattering).” Without the
perceived ability to exert an influence on his heart rate, or to see his heart rate increase or decrease based on his behavior, he found it less interesting to track his heart rate or to analyze the resulting data.

Conversely, his sleep data had tremendous amounts of variability, which he indicates (in line 4 of the passage above) that he considered to be more interesting. Just as the preceding passage, this passage was coded as “Variability (reason for mattering).” Admittedly, phrases such as “I don’t know, I guess…” make it seem as though he is inventing reasons for his prior answers, and that he has not given much thought to his answers before now — Russ, Lee, and Sherin (2012) argue that this sort of hedging suggests that the participant is engaging in an ongoing sense-making while responding to the interview questions. However, using the constant comparative approach to coding led me to notice responses with similar themes in interviews with other participants; Greg’s responses here thus fit with and make sense within a larger pattern in the data, in which the interest that participants expressed in data was contingent on the variability of the data, and their ability to attribute at least some of that variability to their own choices and behaviors. In any event, this passage illustrates some of the coding practices that took place during this round of coding.

I included in this stage of the coding moments where participants explicitly talked about the data being interesting, important, meaningful, or consequential to them in some way, as well as moments where there was apparent (but non-explicit) interest in the data. During these latter examples, I had to make informed inferences about the reasons they found the data interesting, based on the context as well as prior and later statements made
by the participant. In the following example, Kristen has conducted an analysis in which she asks whether her computer usage on weekends is similar to her computer usage on weekdays. She has just calculated the means and standard deviations for her two samples (weekday computer usage and weekend computer usage), and the difference in means was a little less than 900, and the standard deviations of the two samples was 4599 and 3499, respectively. The following passage is included to provide some context for an additional passage quoted later.

Jeff: So let's compare our means. Based on what you are looking at there, do you think you would reject the null hypothesis?

Kristen: [Pondering.] Do I use it more for entertainment on weekends than on weekdays?

Jeff: So the null hypothesis would be...

Kristen: That I use it the same.

Jeff: So looking at your two means here, do you think you can reject the null hypothesis?

Kristen: No.

Jeff: Why not?

Kristen: No, yes.

Jeff: Yes? Why do you think that?

Kristen: Because they are way different. And because the weekend is more than the weekday. Well, not by that big of a standard deviation. Yeah, it would be a very, very small fraction of the standard deviation. But yeah, anyway.

Jeff: So you think you can?

Kristen: Yeah. (Second data exploration meeting, June 12, 2015, 00:23:50)

In the preceding passage, Kristen made a prediction, based on the difference in means of the two samples, that the null hypothesis will be rejected and that she uses the
computer usage on weekends differently than on weekdays. While she (rightfully) compared the difference in means with the magnitudes of the sample’s standard deviations, she still concluded that the difference in means was large enough to indicate a difference between the samples. After conducting a t-test using R programming, she determined that the p value was actually close to .55. The following conversation ensued:

Kristen: So this could be interpreted by saying, "This is like a 55% chance..." [trails off]

Jeff: "... of getting this difference in means if the null hypothesis were true."

Kristen: Wow! [Pause.]

Jeff: So was anything unexpected here? Does anything surprise you?

Kristen: I thought that we were going to reject it, because 700 seems like a big number to me. Actually, it's almost 800. But I was also looking at... Was I right, was I onto anything when I was saying that because the standard deviation is so big, it would be such a tiny... (Second data exploration meeting, June 12, 2015, 00:29:00)

In this brief exchange, Kristen appeared captivated and deeply surprised by the results. Her posture during this exchange was one that indicated interest — she was leaning forward in her chair, pointing to the values on the screen, and looking back and forth between the values. Her verbal expression of “Wow!” indicated both interest and surprise in the results. For these reasons, I coded this moment as one in which there is potential “mattering,” or at the very least, a strong interest in the results of her analysis. I
also coded it as “Surprise (reason for mattering)”, which I interpreted as the fact that the results seemed to interest her because they violated her expectations.

Later, for example, she indicated that she expected her weekday computers to exceed her weekend computer usage, because she believed that she engages in more outdoor activities on the weekends. So these results contradicted expectations that she had of her data (expectations based on both her interpretation of her initial data analysis and her recollected experiences). This contradiction of her expectations seemed to catch her interest, and to involve her in a deeper examination of both the numbers on the screen and their potential implications. She seemed invested in discovering why her prediction was wrong, evidenced by her returning to and re-evaluating her earlier reservations about her predictions (which were based on the comparison between the difference in means and the relative standard deviations of the two samples).

The above example illustrates the process of coding implicit moments of interest and mattering, wherein I used the words of the participant, their posture, and their activities to infer when some aspect of the data or data analysis was of specific interest to them, and wherein I used the context of the exchange, as well as prior and later statements by the participant, to make inferences about why that moment was so interesting to them. Using comparable techniques, I coded not just moments of explicit mattering and interest, but also moments of unstated, implicit mattering and interest. In either case, during this stage of the coding and analysis process, the statements of the participants were taken at face value — unless there was specific contradicting evidence, I interpreted their explicit statements that the data or data analysis mattered to them at
factually representing their concernful engagement with the data analysis (as well as the reasons they gave for this mattering).

**Axial coding**

After the initial pass of coding, I had a list of 15 possible reasons that data, or the data analysis process itself, seemed to matter to participants (or, at the very least, be interesting to them), which can be found in Table 4. After this initial pass, I then engaged in axial coding, which is a second-pass coding strategy described by Saldaña (2015) as an approach that “reassembles” what initial coding can break down; Glaser (1978) argues that axial coding is processes in which the “code is sharpened to achieve its best fit” (p. 62). When conducting axial coding, a researcher will look at the “mess” of codes produced by an initial coding pass and attempt to relate each code to a larger category, and to identify and define the boundaries of larger categories that may be more useful than each individual code.

Two of these entries in the list produced in my initial coding pass pertained to only one instance in the data each, and several others pertained only a handful. While such unique instances can provide useful information (and I did examine them more deeply later on), at this stage in the analysis, I was more interested in reasons that were expressed or found in the experiences of the most participants — that is, broader themes that could be discussed as common amongst the narratives of the learners. I took each item on the list that could be found in the experiences of at least 5 of the participants, and examined them more closely. I chose this threshold in part because it reduced the number of elements to a more manageable size, and because items found in the experiences of
fewer participants seemed to be cases special to the particular backgrounds of the participants. At this point, I began to construct themes based on these codes. I will highlight here some examples of how these themes were developed.

Table 4
Initial List of Codes for Reasons for Interest or Mattering

<table>
<thead>
<tr>
<th>Reasons for Mattering</th>
<th># of participants</th>
<th># of instances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desire to Change</td>
<td>7</td>
<td>38</td>
</tr>
<tr>
<td>Have a Problem</td>
<td>7</td>
<td>23</td>
</tr>
<tr>
<td>Confirmation</td>
<td>7</td>
<td>22</td>
</tr>
<tr>
<td>About Myself</td>
<td>7</td>
<td>20</td>
</tr>
<tr>
<td>Surprise</td>
<td>7</td>
<td>19</td>
</tr>
<tr>
<td>Affects Aspects of Life</td>
<td>6</td>
<td>31</td>
</tr>
<tr>
<td>Moral Valence</td>
<td>6</td>
<td>21</td>
</tr>
<tr>
<td>Variability</td>
<td>6</td>
<td>19</td>
</tr>
<tr>
<td>Ability to influence</td>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>Just interesting</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Related to profession</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Novelty</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Hobby/passion</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Interesting because optional</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Interesting because trivial</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

By examining instances of each code, I determined that “desire to change” and “have a problem” were closely related, and that while some theoretical distinctions can be made (someone can want to walk more without seeing their lifestyle as deeply problematic at present, for example), there was enough overlap to make the distinction difficult to justify in each and every instance. Moments that were unambiguously “a
desire to change” rather than a perception that they “have a problem” were sensibly recoded as “moral valence.” In addition, “affects other aspects of life” and “ability to influence” were also closely related. “Affects other aspects of life” was a code that referred to when the ups and downs of the data seemed to matter because they influenced others aspects of their life. For example, one participant (Brian) found his sleep data to be more meaningful than his step data, because he believed that the quality of his sleep had a more noticeable impact on the way he experiences life:

Jeff: What do you think makes this question more important, or matter more to you than the previous ones?

Brian: Because sleep, more so than the other things, affects quality of life. If you don't sleep very well, you don't have good quality of life. Whereas I'm not sure I'm convinced that if you take 5,000 steps or 10,000 steps that really affects anything in terms of day-to-day. I'm sure it does in the long-term, as exercise and stuff, but. I think sleep would be interesting because I think it affects your life more than some of the other things, at least in your experience.

(Final interview, August 21, 2015, 00:29:16)

In this example, Brian found his sleep data meaningful because of the implications that his data might have on other aspects of his day-to-day experiences. Similarly, Greg, in the earlier example provided, felt that his heart rate data was less meaningful because he felt that there was little he could do to effect his heart rate data; regardless of his daily physical activity, it appeared to him that his heart rate was rather stable. I coded this as “ability to influence.” Both of these constructs seem deeply related
— in either case, the aspect of the participant’s life that is being tracked is perceived to be in a causal relationship with other aspects of the participant’s life; in the case of “affects other aspects of life,” the item being tracked is perceived as influencing some other aspect of life, and in the case of “ability to influence,” the item being tracked is being influenced by some other aspect of life. In both cases, the perception is that some aspect of the data is under the control of the participant, and tracking and analyzing the data is perceived as informing the participant’s choices.

“Confirmation” and “surprise” were unique in that positives instances of one were negative instances of the other; but both were coded at various times as reasons for mattering. There were moments in which the participant felt invested in ensuring that his or her predictions were accurate (confirmation), and moments in which the participants were invested in exploring why they were not (surprise). A possible explanation of this may be that data matters when learners can form expectations, regardless of whether those expectations are met — perhaps the ability to form hypotheses about the data based on intuition or personal experience is enough to make the data more interesting, while the lack of such an ability makes the data less interesting. This will be examined later.

The instances coded as “about myself” were difficult to analyze, because a number of instances coded as such seemed to be instances where the data mattered for more reasons than just because it was about the self — for example, a participant might say (this is a fictional example), “It’s interesting because it is about me,” but then follow it up immediately with, “and I want to change that aspect of my life,” making “desire to change” a more fitting code for that instance (even though “about myself” was attached...
to the first clause of the sentence). Other instances where the data was interesting or mattered only because it was about the self seemed contrived, as there were cues that the participant was saying only what they thought I wanted to hear (correctly assuming that I am testing the use of self-data in statistics learning). In the end, the number of instances where the code seemed to more fully or genuinely apply fell below the threshold I had set for this stage of the analysis.

I then completed a second pass of coding the data, this time including video of the data exploration meetings as well as the initial and final transcripts. Using similar procedures as before, I coded instances in which participants explicitly discussed the way in which the data and data analysis mattered to them, as well as implicit moments where they seemed to be more engaged with the data. This time, however, I used the codes included in Table 5 as my updated coding scheme, and instances in the data were coded as illustrating these dimensions (as either positive or negative examples). Broader themes generated from an analysis of this subsequent coding will be presented later in the paper.

Table 5
Final List of Codes For Reasons for Mattering/Not Mattering for Second Coding Pass

<table>
<thead>
<tr>
<th>Reason for Mattering</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Moral valence</strong></td>
<td><strong>Example #1:</strong> I like to use weekends to catch up … on sleep, but I don't want to use weekends just to be lazy (Britney, final interview, June 23, 2015, 00:20:02). <strong>Example #2:</strong> I kind of wish it had said that I used it more on weekdays than on weekends. … I guess if that was the answer… it could mean that… I'm not having as many adventures as I think (Kristen, final interview, June 24, 2015, 00:40:23).</td>
</tr>
</tbody>
</table>

Instances where the data seemed to be of interest to learners because it has a moral valence, that is, where ups and downs are taken as more or less preferable. For example, high heart rate may be interpreted as problematic, while low heart rate may be seen as preferable. A low daily average for steps might be interpreted as something warranting a change; a high daily average for steps might be celebrated.
Table 5 Continued

***Variableness***

Instances where the data seemed to be interesting or important in part because it was variable; most often, this was observed in the negative, where data was considered less engaging because it was *not* variable.

**Example #1:**
Jeff: What do you think would've made your mood more interesting to you to track?  
Sara: I don't know, just having it be different every day. But it really wasn’t (Sarah, final interview, September 2, 2015, 00:26:30).

**Example #2:**
Jeff: So why was heart rate not as interesting to you as you thought?  
Greg: I guess because I didn't see that it fluctuated, so there wasn't really anything, to me, that correlated as much with it, and so I was taking more steps, but my heart rate still stayed the same, or things like that. So it just didn't strike me as interesting enough to follow it I guess (Greg, final interview, August 21, 2015, 00:06:48).

***Have a problem***

Instances where the data seemed to matter because the participant believes they have a related problem in their life that warrants scrutiny of the attribute in question. For example, steps might matter because of a recent knee surgery, or heart rate might matter because of a heart problem. This also includes examples where the participant feels as though they have bad habits or lifestyles they wish to change. For example, steps might be important because the participant wants to walk more and “veg” less; or conversely, steps might *not* be important because the participant already walks a great deal.

**Example #1:** So I care about my steps because I'm still recovering from this knee problem. So I care about that (Britney, initial interview, May 13, 2015, 00:26:52).

**Example #2:** I think I would be more interested in tracking phone than computer, because my phone is something that I'm trying to use less, but my computer isn't (Brian, final interview, August 21, 2015, 00:16:43).
### Table 5 Continued

#### Ability to control
Instances where the data seemed to matter because of correlations or effects the tracked attribute may have with regards to other aspects of their life. These correlations may give the perception that the participant has influence over the aspect being tracked, or that the aspect being tracked might grant them influence over something else. For example, sleep might matter to a participant because it might affect mood or focus; conversely, heart rate might not be interesting because it “doesn’t affect anything else.”

**Example #1:** It might have been interesting to do mood and sleep, or mood and steps. … People say things like, when you exercise more you have a better mood, so it would be interesting to see if it's true (Brian, final interview, August 21, 2015, 00:13:54).

**Example #2:** That matters, because I know that using the computer a lot is kinda bad for me, and I know that sleeping a lot is good for me, and if... I would want to know the relationship between those. Like if computer usage (that I know is really bad for me) also affected my sleep, then it's even worse (Kristen, final interview, June 24, 2015, 00:41:56).

#### Validating or contradicting expectations
Instances where the data seemed to be interesting or important because it violated the participant’s expectations, or instances where the data seemed to be interesting or important because it confirmed the participant’s expectations.

**Example #1:** Personally, I thought if we looked at the sleep times [e.g., bed time and wake time] it would be different [e.g., significant results]. But, for sleep duration, I thought... I usually stay up late on my phone, just like, playing games and wasting time. I believed it would affect the sleep duration more, but I guess I just slept in the next day, and that kind of made up for that (Chris, final interview, June 24, 2015, 00:32:26).

**Example #2:** [I]t was also really interesting to see how long I slept. Cuz I thought I only slept 8 hours, but it seemed like it almost averaged out more to a high 8, to almost 9, hours of sleep a night (Peter, final interview, June 24, 2015, 00:13:54).
Uncovering Participant Narratives

Because learning as embodied familiarization (which treats learners as concernfully involved and fully embedded within a social context) calls for a narrative orientation in analysis and discussion, my first priority was to develop a thick description of each participant’s involvement with the study in narrative form. As Saldaña (2015) explains, one of the tasks required when adopting a narrative orientation is to produce a write-up that includes “rich descriptive detail and a three-dimensional rendering of the participant’s life, with emphasis on how participant transformation progresses through time” (p. 134). This detail-rich narrative should help us to understand the participant’s actions as situated within the context of a larger, unfolding story.

One of the interview prompts (“I’m wondering if, to start with, you can tell me the story of your participation with this study, from beginning to end”) was designed to elicit the participant’s version of their participation with the study, in order to enlist their help in understanding their story. However, this question turned out to be deeply inadequate — most participants provided answers that did not constitute a fully-fleshed out narrative, and dealt almost solely with dry facts (“I did x and then y”), without much detail about their objectives, difficulties, attitudes, etc., that would enrich their story and give insight into their concernful involvement in the activities they described.

In addition, during the initial coding, I noted in my coding memos a number of instances in the data where learners seemed to be striving towards particular objectives, and where they had hopes and expectations of the future (and how learning statistics played into their projected futures) — in other words, instances that hinted at the larger
life-story of the learner, in which their participation in this study is situated. However, my initial coding schemes were not built to accommodate this sort of narrative-building, nor did it systematically make use of the narrative emphasis called for by my theoretical orientation. For these reasons, I began to explore coding schemes used in other narrative-focused studies.

On the second pass of coding, I borrowed significantly from *dramaturgical* and *values* coding schemes (as described in Saldaña, 2015; Gable & Wolf, 2012), which allowed me to mark instances in the transcripts that corresponded to different aspects of the learners’ narratives. These narrative-based coding schemes are described by Saldaña (2015) as intrinsically compatible with each other, as each can augment the findings of the other. A list of codes used in these coding schemes can be found in Table 7.

Table 6
*List of Codes Used for Dramaturgical Coding*

**Dramaturgical Coding**
- Objective
- Conflict/Obstacle
- Tactics/Strategies
- Emotions
- Subtexts

**Values Coding**
- Values
- Beliefs
- Attitudes
**Dramaturgical Coding**

Dramaturgical coding superimposes terms and concepts associated with play scripts onto interview data, and treats interviews as describing (and as part of) an ongoing “social drama” (Saldaña, 2015). In other words, dramaturgical coding treats the interviewee as a character within a story, a character who has objectives, encounters obstacles or conflict (which drive the plot), employs strategies for responding to those obstacles, etc. — all-important elements in script writing and analysis. Dramaturgical coding assumes that the motives, emotions, attitudes, and conflicts of the characters are not always explicitly included in the script, but that readers and audiences will pick up on those elements of the drama nonetheless (or else they will be unable to follow the story), based on the dialogue-in-context, aided by the actors’ facial expressions and gesticulations. Dramaturgical coding is a process by which the researcher can make similar inferences and justify those inferences based on the text (Cannon, 2012).

Patterson (2013) notes that narratives offered by participants in interviews and conversations with researchers do not always flow in temporal order; I observed the same in my interviews with the participants of my study — even when prompted to tell the story of their participation in temporal order (“from beginning to end”), their responses did not constitute a fully-fleshed out narrative. When explicitly asked to tell the story of their participation, participants did not include much detail about their objectives, difficulties, attitudes, etc. — details that are necessary for a “thick” description of the learner’s experiences. Dramaturgical coding, however, helped me to identify these other details when expressed elsewhere in their interview transcripts, and to stitch those aspects
into a time-ordered, rich description of their experiences. In this way, the use of
dramaturgical coding helped me to develop and articulate each participant’s story with
respect to their participation in the study and their experiences with self-data.

As I was coding, there were numerous instances in which aspects of the “drama”
were implicit, rather than directly stated. This fits with the assumption of dramaturgical
coding that vital elements of the drama is inferred by the audience based on the dialogue-
in-context, and not directly stated in the dialogue itself. Consider, for example, the
exchange below, which richly illustrates this process of dramaturgical coding (Sarah,
final interview, September 2, 2015, 00:07:20 - 00:07:28):

66 Jeff: How are those going for you so far?
67 Sara: Good. I actually understand stuff, it's
great!
68 Jeff: Cool! What do you think contributed
the most to that? Because you act surprised
that you understand it.
69 Sara: Yeah, because last semester I was
really freaking out in the Spring, because I
knew I had to take a few more stats classes,
because I'm a math-stats major, and that
had changed during that semester because I
was going to do just math and then biology
teaching, but Utah State doesn't have a
biology teaching minor, so I have to do
math and stats, so I was like "Ok, I'll just
push my way through and make sure that I
do well enough that I don't have to re-take
classes." And then over the summer I took
this class, and it wasn't what I was
expecting. It was harder than I thought, and
I got a C, but I passed and that's all that's
important right now. But it was interesting,
because the stuff that we did in here made it
more concrete in my mind.
First of all, in line 59, Sara’s emotional state is conveyed in her tone of voice, her facial expressions, as well as the words she says. For example, her statement that she “actually” understands stuff implies an expectation that she would not, or at least that she did not for a time. Her tone of voice and facial expression conveys a sense of excitement, with a slightly elevated volume accompanied with a smile. She is both surprised and excited that she feels like she understands what she is learning in her statistics course.

Next, she indicates that this emotional state is in contrast with a prior emotional state — a few months prior, she was “freaking out” about needing to take more statistics courses. This word choice, in context, seems to convey a state of fear or anxiety experienced when stepping into a future that involves taking more statistics courses. The statistics course itself is implied by this to have been treated as an obstacle in her story, a source of conflict in the way of her objectives. This is illustrated by her use of the words “push through” when talking about how she saw her statistics course — the statistics course disclosed itself as an obstacle in the way, almost like thickets and foliage across her path, impeding her progress.

In addition, we have evidence here of Sara principle objective: completing her degree and moving on with her life. This is implied in her statement of her strategy of making sure that she does well enough that she doesn’t have to re-take classes, and her statement, “It was harder than I thought, and I got a C, but I passed and that's all that's important right now.” What is unstated but implied in this statement is that passing the course is all that is important when considering an objective of completing her degree — if her objective was to thoroughly master statistics (or some similar goal), a C grade
might have been more alarming to her. That this is her primary objective in taking the course is highlighted by other statements made by Sara that she believes that statistics will play no role in her future professional life, and that she is taking the course only to complete degree requirements. A subtext in this exchange is that while the course was indeed as difficult as she expected (if not more), her former anxieties were unfounded — she can understand more than she expected to, and subsequent conversation reveals that, while she still does not see statistics as playing a substantial role in her future profession, she can better understand why it might be important for and useful to others.

Dramaturgical coding, in this example, helped me to make informed inferences about Sara’s personal narrative, rich with details about her objectives, emotions, etc., as well as the role the statistics course plays in her narrative (in this case, as an obstacle in her way). In a similar fashion, dramaturgical coding helped me to uncover the role that participating in this study, as well as using self-data to practice statistical concepts, played in her personal narrative. Dramaturgical coding, in this way, made it possible for me to discover and articulate narratives that were far more thick with details about the participants’ motives, objectives, emotional experiences, conflicts, etc., than I would have been able to relying on the transcript alone — and to better justify such inferences using the transcripts of the interviews and data exploration meetings.

Value Coding

The use of values coding also helped me to “thicken” the narrative surrounding each participant’s experience with the study. When engaging in values coding, the researcher codes interview transcripts for evidence of values, attitudes, and beliefs. In the
context of this study, *beliefs* are understood to refer to a learner’s *ideas* about the subject matter (e.g., “Statistics is not helpful for math teachers), whereas *attitudes* are understood to refer to “relatively stable, intense feelings that develop as repeated positive or negative emotional responses are automatized over time” (Gal, Ginsburg, & Schau, 1997). In contrast to both, *values* are understood to refer to those things, persons, or ideas that a learner attaches great importance to. A learner *values* something when he or she attaches great significance or personal meaning to it, and treats it as having importance in his or her life (Saldaña, 2015).

Traditionally, the “attitude” code is included in dramaturgical coding, but I left this code out precisely because I planned to code for attitudes as part of *values* coding. McLeod (1992) proposed that *attitudes, beliefs*, and *emotions* be jointly considered and coded for in qualitative data when considering mathematics learning, a process very similar to values coding (but in which *values* are replaced with *emotions*). Combining values coding with dramaturgical coding — which codes for *emotions* — allows me to include each of these as potential codes when examining the data. I have included *value coding* here as a separate coding scheme — despite its significant overlap with dramaturgical coding, because I wish to highlight the distinct coding traditions that contributed to the qualitative analysis of this study.

A potential danger of *value coding* is that it could be used to treat a learner’s attitudes and values as endogenous variables to be discovered in the data — an approach specifically rejected by my principle theoretical orientation. However, the purpose of including value coding in this study is to further flesh out and “thicken” each learner’s
personal narrative. When combined with dramaturgical coding, identifying a learner’s values and attitudes — or, to use wording more congenial with learning as embodied familiarization, exploring what learners value as well as the emotional tenor of their engagement with the learning activities (attitude) — can help me to explore the nature of his or her concernful involvement with respect to the learning material and activities.

Further, as I explained earlier, learning activities are conceptualized in this study as “mattering” to a learner when a learner perceives or believes that the future will unfold differently (in ways he or she does not wish) if he or she does not engage in the learning activities; to get at mattering, then, it may be valuable to understand participant’s beliefs about the future and how the future will unfold based on his or her actions in the present. In addition, on a theoretical level, I believe that we sometimes engage with activities not because we are instrumentally pursuing objectives, but because we value some aspect of the activity. Our concernful involvement in an activity is not always directed towards an explicit objective, nor our activities always conceptualized as a means to an end. Including values as part of the personal narratives of the learners may help me to avoid forcing aspects of the learners’ concernful involvement into an instrumental narrative in which learners are engaging in activities always and only as a means to an end.

As with dramaturgical coding, a learner’s beliefs, attitudes, and values may be evidenced by direct or explicit declarations of the learner, or inferred based on the learner’s dialogue-in-context, supported by exploring the learner’s facial expressions, tone of voice, gestures, situational cues, and other statements made by the learner. Consider, for example, the following exchange:
Jeff: So tell me, what are you studying in school?

Kristen: Ecology.

Jeff: So tell me about how you got into Ecology?

Kristen: So, I started out in Anthropology. And I was kind of realizing that it is a field that there is such low demand for it that I would have to be the best ever until I really like either, you know, to be successful. And then I was just kind of realizing that I was also kinda of like super super interested in the environment, and I think I can, like, there's more job security and there's a lot more that I can do to benefit people if I'm at work, and so I switched.

Jeff: So, is there a higher demand for ecologists?

Kristen: I'm pretty sure.

Jeff: Ok. What interests you about the environment?

Kristen: At a very basic level, it's literally everything that we have. Like, all that we have. I kinda want to combine anthropology and ecology with my work. It's going downhill right now, and there's going to be a lot of people who are refugees from environmental disasters, or flooding, or anything like that, so I want to combine the knowledge of both to help people at a local level either adapt to or prevent problems. (Kristen, initial interview, May 7, 2015, 00:04:22)

In the above example, values coding helped me to justify my assertion that Kristen believes that catastrophic climate change will create a need for ecologists and the
work they do. This projected future, it turns out, informs Kristen’s concernful involvement in the learning activities. Throughout later interviews with Kristen, for example, she frequently refers to statistics as something that she expects to be vitally useful to her as a future researcher in ecology, with the hope that her involvement in the discipline can help others as the effects of climate change unfold. Identifying Kristen’s beliefs in this regards — and the value she places on helping others — lent insight into the nature of Kristen’s concerns, her personal narrative with respect to her participation in the statistics course, and how and why learning statistics matters to her as a student.

In addition, her positive attitude about the environment also helped me to understand her choice to study ecology — at one point later in our conversations fantasized about working outdoors in a tropical environment. She has, in a sense, romanticized the notion of working for environmental causes, and projects a future in which she will be engaged in beautiful outdoor contexts, having adventures close to nature. This positive attitude towards the environment helped to contextualize a later exchange in which she was disappointed that her weekend computer usage was not significantly lower than her weekday computer usage, because it signaled to her that she may not be having as many outdoor, active adventures as she thinks — she places a positive moral valence on physical, outdoor activity, and a negative moral valence on sedentary, indoor activities.

While these beliefs, values, and attitudes may be inferred from a careful reading of Kristen’s comments without coding, value coding allowed me to systematically justify those inferences based on specific references to the transcript. Combined with
dramaturgical coding, this helped me to develop “thick” articulations of each learner’s personal narrative with regards to their participation in the study and their concernful involvement in statistics learning activities. Both helped me to discern what they were concerned about and what mattered to them as they engaged in those activities.

**Articulating the narratives**

After coding the interviews, I consolidated instances in the data to help piece together these narratives; for example, I gathered all coded instances of “objective” into one place, and identified the various objectives pursued by the participants. I gathered all coded instances of “obstacle,” and tried to figure out (based on context) with what goals those obstacles were interfering, and which of the coded instances of “tactics/strategies” were intended to help overcome those obstacles. I similarly gathered all coded instances of “attitude” and “values” to determine what was important to the learners, and their affective comportment with respect to elements of their story.

In this way, I was able to stitch together an informed articulation of each learner’s story, even if they did not explicitly tell me the story in temporal order or with thick descriptions of their motives and internal experiences during our interviews and conversations. Each learner’s narrative was distinct, in ways that were revealed more clearly through the combined process of dramaturgical and values coding. Here are brief outlines of several of the narratives of the participants in the study:

**Britney.** Britney’s primary objective was to help at-risk learners get access to academic tools and resources; the principle obstacle in her way was her lack of experience in statistical inquiry, which she believed essential identifying at-risk learners;
her strategy to overcome this obstacle was to take an undergraduate statistics course, wherein she encountered my study. Her initial goal in participating in the study was to help me as a researcher, but this goal shifted as she realized that analyzing data about herself could help her overcome her lack of experience in statistical analysis. The data exploration meetings became centered on her realizations of how she could perform similar analyses to help her target her interventions towards at risk learners.

**Sara.** In contrast, Sara’s primary objective was to become a math teacher; the principle obstacle in her way was the requirement that she take a statistics course, which she saw as an unwanted burden. This is because she did not believe that she would be using or teaching statistics as a math teacher. She participated in the study was because she wanted to track aspects of her life, and to try out the devices offered; however, during the self-data exploration meetings, she discovered how statistical tests (such as t-tests or correlations) could be used to answer real research questions. An unspoken subtext in her interviews what that her anxieties and fears about statistics were resolved in large part due to her experiences exploring her own data, as she discovered how statistics could be useful as an instrument of inquiry.

**Kristen.** Kristin believed that catastrophic climate change will create a need for ecologists and the work they do, and so that by becoming an ecologist, she would be guaranteed a rewarding career of helping others. Because she believed that ecologists use statistics as an integral part of their professional practice, Kristen sees taking statistics as a tactic or strategy for pursuing this long-term objective. Kristen’s stated reason for participating in this study was the compensation, but she implicitly saw the study as an
opportunity to overcome her habit of becoming absorbed in mindless, online entertainment, by tracking her computer usage using RescueTime. While exploring the data using statistics was not as revealing or habit-breaking as she hoped it would be, in her case, the self-data and data exploration meetings became a proximate, personal application of the statistics she was learning.

**Brian.** Brian was preparing to pursue a graduate degree in economics, but was generally weary of the discipline. While his colleagues in the discipline used statistics heavily in their work, Brian deliberately steered clear of statistical activities, and hoped to continue to do so in the future. His career ambitions were at best hazy, and the role that statistics would play in his future career was also hazy. His participation in the course was motivated by a desire to complete his major, and his participation in the study was motivated by the compensation and idle curiosity. Brian’s experience with tracking his own data did not situate statistics as a useful tool for inquiry — not only was Brian ambivalent about his future career aspirations, he was ambivalent about each aspect of his life that he tracked and analyzed.

**Peter.** Peter was completing a degree in Nutrition Science, and hoped to enter medical school after he graduates. Like Brian, Peter struggled to articulate more than a vague idea of how statistics would be useful to him in his professional pursuits. This vague projection of the future made it difficult to see statistical inquiry as anything more than homework. However, Peter also had ongoing troubles with his sleep, and tracking his self-data offered to provide him insights into those sleep troubles. While he ultimately learned little about those sleep troubles, using statistical inquiry to explore his sleep data
positioned statistical inquiry as a tool for answering questions about his world, and provided him with a more concrete, proximate context in which statistics is potentially useful to him.

These examples illustrate the unique and individual narratives that dramaturgical and values coding helped me to stitch together using the transcribed interviews. None of these narratives were directly stated in the interviews, but rather were implied as illustrated in the coding examples above. It is clear from these narratives that the mode of each learner’s concernful engagement was different; that is, that each learner had different objectives, different concerns, and that the exploration of self-data using statistics served different ends for them. That is, we can make the case that the self-data mattered to them differently. A deeper discussion of these results will take place in the results section.

Thematic/Theoretical Coding

In addition to dramaturgical coding, I also coded the data for “themes” suggested by both my theoretical orientation and my first pass at coding the data. This coding process involved a combination of theoretical coding and thematic coding. Thematic coding is sometimes treated as a subset of narrative coding, in which the researcher explores themes within the participant’s personal narrative, as they would a work of literature. It can also be treated as a stand-alone coding strategy, in which larger sections of the code can be labeled as illustrating a particular theme that cannot be attached to single statements or utterances by the participant (Saldaña, 2015).
According to Saldaña (2015), these themes “may be identified at the manifest level (directly observable in the information) or at the latent level (underlying the phenomenon),” and can consist of larger theoretical suppositions or explanations, rather than merely descriptive terminology (p. 267). At this stage of the process, I combined this thematic approach with theoretical coding, which is an approach in which the researcher can either examine segments of data and codes using pre-existing theory as an interpreting framework, or develop theory based on the codes and the data (and then use that theory as a code for the data). In this case, I adopted some of both approaches.

These themes include *problematizing the familiar* and *concernful involvement*. The first two are suggested by my theoretical orientation, and I thus used them to help structure my interpretation of the data. The third was suggested by the data itself. I coded any instance in the data that seemed to lend support to or which could contradict these themes.

**Problematizing the familiar**

One of the central constructs of *learning as embodied familiarization* is the distinction between *ready-to-hand* and *present-at-hand*. When *ready-to-hand*, the phenomenon itself is invisible to us, as the steering wheel as one makes a routine turn while driving. This could also describe the phenomenological qualities of something that is “familiar” to us — our antecedent familiarity serves as the invisible backdrop against which our involvement in the world takes place. However, we could *make* the steering wheel “occurrent” or “present-at-hand” by asking the driver to focus on the feel of the wheel beneath their hands, the resistance of the wheel as it turns, the motion of their
hands through space as they turn, etc.; in doing so, we are inviting them to change their comportment with respect to the object.

Similarly, there are aspects of our physical activities and embodied experiences that are similarly “invisible” to us; we do not normally think about the number of steps we take, or our heart rate, or even on most days our sleep patterns. These things happen and are an integral part of our embodied experience, but they are normally taken “ready-to-hand.” Even those who track their steps regularly might find many aspects of their step data to be invisible, including patterns with regards to when they walk and do not walk; what is *occurrent* to them is often only the total number for each day — whether they met their daily target. One of the affordances of physical activity trackers is the ability to make the “familiar” “unfamiliar,” that is, to make these sorts of phenomena “occurrent” to learners, to afford the opportunity to answer questions about their daily activities that they may never have even thought to *ask* before.

In some ways, it might be like asking someone “at home” in their kitchen (using our earlier example) to ponder on the layout and organization of their drawers, and to thereby step into new concerns (such as the efficiency of the layout) that they had not encountered before. In some ways, the hope of this project is that using self-data will connect to learner’s pre-existing concerns, *and/or* invite the learners to step into and take ownership new concerns — and by so doing, involve themselves in statistical analysis in ways that disclose statistics as an instrument of inquiry (that is, as a way of numerically investigating the world, and thus more than merely a means for getting a grade or pleasing a teacher).
This idea of “problematizing the familiar” may, then, be integral to the intervention of using self-data in a statistics learning context — and perhaps one of the linchpins of the success of the approach is that it invites learners to ask new questions that they might not otherwise ask (or be able to answer). If, for example, an individual tracking his or her sleep does *not* find any questions to ask about their data, then engaging in statistical analysis will not reveal itself as an instrument of inquiry to the learners — but rather, just as in class exercises, as a drudgery performed for the sake of some other interest (such as pleasing the teacher or the researcher).

On my first pass through the data, I noted (but did not code) a number of instances in which it appeared that learners were asking questions about their physical activities that they might otherwise have not though to ask, or stepping into concerns about aspects of their life that were at one point mundane and familiar — in other words, I coded for instances in which the *familiar was problematized*, or where this theme was touched on in some way. Here is an example of this coding process, taken from the final interview with Brian:

```
Jeff: Ok. So are there other questions we could've asked about your steps, do you think, that would've mattered to you more?
Brian: I mean maybe; I don't know... yeah. It's just that none of the things on the list are things that I think about really that often. I'm never like "I wonder how well I slept last night!" Or something like that. So I think they're more just interesting. (Final interview, August 21, 2015, 00:25:11)
```

Code: Problematizing the familiar (negative example)
In this example, what was familiar to Brian was not made unfamiliar to him; he did not find himself asking questions about his steps, or stepping into new concerns as a result of tracking his steps. This may be an example of where the self-data failed to make the learning exercises matter more to Brian, precisely because the familiar was not problematized in this way — his daily activities were not made occurrent to him, except in the moments required by our interviews and data exploration meetings. Here’s another example from the final interview with Sarah:

I thought that I would be pretty consistent with my steps, but some days was a lot, and some days was not very much. And I wasn't expecting that. So it was interesting to see if I could remember if something had happened that had increased my steps or decreased it, like when I hurt my foot I didn't walk around. Or if I went for a really long run, then it was more. I guess I never really thought "Oh, I'm taking more steps today." or "Oh, I'm not walking as much today." So it was interesting. (Final interview, September 2, 2015, 00:24:35)

In this example, Sara explicitly describes her physical activities as being “ready-to-hand” — at the time, she was not thinking, “Oh, I’m taking more steps today.” It was after the fact that she began to notice patterns and variability in her daily activities, and because to ask questions about events that may have contributed to that variability. This is an example of problematizing the familiar. Other instances of this theme were coded in a similar manner; while some judgment and discretion is required at this stage of the coding, each tagged example will be included and justified in the results section.
Concernful involvement

The purpose of this study is to see whether self-data can invite learners into new modes of concernful involvement, where they engage in data inquiry because the answers are meaningfully important to them. The hope is that by doing so, statistical concepts will disclose themselves as *instruments of inquiry*, rather than as burdens, obstacles in the way of getting a grade or passing a classes. During my first pass at coding the data, I noted (but did not explicitly code for) instances in the data that seemed to illustrate this theme. This is perhaps because these instances were often implicit rather than explicit, and also involved longer segments of transcript, which made it more difficult to code specific phrases or sentences that were illustrative of this theme.

During my second pass in coding the data, I coded excerpts from the transcripts as “concernful involvement” if those excerpts seemed as though they may yield insight into understanding this theme. This included passages that hinted at learners’ concernful involvement disclosing statistical activity as instruments of inquiry, as well as passages that hinted at concernful involvement for the sake of passing a class or pleasing the researcher (in other words, both positive and negative examples). In short, I tagged passages that hinted at the concerns of the learners as they were involved in the practices of the study, or discussing with me their experiences, and how the use of self-data may have influenced those concerns.

For an example of this process, consider the following excerpt from Sara’s final interview. Sara had just expressed that tracking her heart rate and her breathing would be
more interesting to her now (at the end of the summer) than before (at the beginning of
summer). She explains:

Sarah: Not necessarily. I think heart rate
would be interesting to track now. And
breathing. Yeah, this could be interesting.

Jeff: Why would they be interesting?

Sarah: Well, I started going running half-
way through the summer, and because of
health reasons I haven't been able to the
past two and a half years, so it was like
"Yes, I can finally work on my fitness."
And then it would be more interesting to
do those types of things, which wasn't the
case in May or in the beginning of summer.
So I was like "Yeah, that's not really
interesting." But now, it's like "Yeah, that
would be interesting to track." Because I've
gotten into fitness more since starting this.
(Final interview September 2, 2015,
00:28:43)

In this example, we see that Sara’s life projects and activities are brought to bear
in the attention she would give to the data; aspects of her life that she did not consider
interesting or engaging at the beginning of the summer were seen as potentially
interesting or engaging at the end of the summer, at least in part because her physical
activities had changed over time. Sara indicates that the kinds of questions she might ask
about her physical activities changed precisely because she began to care more about her
personal health; or, at least, because she was now in a better position to adjust her
physical activities based on the data. In this snippet, she hints that what the data may
reveal about her physical activities may be more consequential to her now, because her
projected futures may differ depending on the answers in a way they could not when she was less able to adjust her physical activities.

A briefer example of the coding process used in exploring this theme can be found in the final interview with Brian. Prior to this excerpt, Brian was describing the projects involved in the course. He explains:

Jeff: Ok. So how interesting was that data to you? The data sets that you worked with in the class.

Brian: Not really. It was just homework. It wasn't that interesting to be honest. (Final interview, August 21, 2015, 00:06:16)

In this example, Brian implicitly indicates the nature of his concernful involvement with the data sets used in class: he saw them as “just homework.” An unspoken subtext seems to be that Brian sees working with those data sets as mattering only because the teacher asked him to do it — that is, the data sets mattered as a means of passing the class, but not much more. The word “just” in this context implies that data sets could be more than just homework, and other comments from Brian indicate that he treated his self-data, to some extent, as mattering in more ways than merely passing a class (although, in Brian’s case, not in ways that engaged him as a learner).
CHAPTER V

FINDINGS: IMPLEMENTATION

In this and the following two chapters, I will present the findings of the study. First, I will detail an example of one of the participant’s experiences with the data exploration meetings, as representative example of how these meetings “played out” in practice. Then, I will present what participants in the study chose to track, as well as some of the practical considerations of using self-data in a statistics learning environment. Then, in the following chapter, I will explore some of the broader themes that I observed in the data, related to the conditions under which data analysis mattered to learners, and under which learners treated statistics as an instrument of inquiry. Finally, in the next chapter, I will present a couple additional case examples involving the personal narratives of the learners, that highlight the way self-data interacted with ongoing concerns of the learners, and invited them into new forms of concernful involvement in the practices of statistical inquiry and data analysis.

Example of Implementation

Each of the participant’s experiences with this study were unique, as each participant had different backgrounds, chose to track different elements of their daily lives, brought different questions to the table, and had different ongoing life projects and narratives. However, as outlined in the Procedures section and in the related Appendices, I was able to standardize their experience (to some degree) so that the data exploration meetings were somewhat comparable for each learner, even if the particular questions
they addressed or data they analyzed were different. The uniqueness of the individual participants’ narratives and experiences with the study cannot be overstated; however, the procedures followed with each participant were similar and as outlined in the procedures section and illustrated (in one case) below.

In what follows, I will detail the events of the experiences of one participant with the study, as a case example to illustrate how the procedures outlined above were implemented in practice. I will first recount sequentially Sarah’s participation in the study, including her initial interview and the three data exploration meetings. This recounting will include what she chose to track about her life (and some of the reasons she gave as to why), what questions she asked about her data, and what she discovered in the course of her self-data analysis. This account will be presented without extensive detailing of my analysis, and it will not include the final interview, most which is presented as part of the subsequent findings section.

The purpose of this section is to provide a practical sense for how the procedures outlined above were pragmatically implemented in a practical context. This case example is illustrative of the experiences of other participants in many ways, including the kinds of questions asked and analyzed, the general sequence of events, the types of conversation between myself and the participant, etc. Comments made by the participant (Sarah) that yielded significant insight into the conditions under which data analysis can be made to matter to participants are omitted, as the focus of this section is to provide a procedural accounting of the events of the study, in order to provide context for the more
substantive analysis that follows for all of the participants (as the procedures were implemented comparable for each of them).

**Sarah’s data tracking and analysis**

**Initial Interview.** Sarah was enrolled in one of the online sections of the statistics courses, and eagerly volunteered to participate in the study after receiving an email invitation from me. In the “additional comments” field of the QSIA (which she completed 12 May, 2015), she replied, “Even though I don't live [nearby], I'm willing to travel [to the university]. Let me know if that is okay. I'm really interested in participating in this study.” She lives around an hour and a half drive away from the university campus (on days with good traffic), but nonetheless expressed a strong desire to participate in the study despite her distance. We arranged to conduct the initial interview over Skype, for her convenience, and to schedule her data exploration meetings around her visits to campus (which she assured me would be frequent). Her initial meeting with me was conducted through Skype, and each subsequent meeting was conducted in person.

My initial meeting (18 May, 2015) with Sarah, through Skype, was fraught with technical difficulties, including missing sound and a couple complete interruptions of Internet service. In addition, at the outset, her responses in the initial interview did not seem to match the enthusiasm for the study that was conveyed in her QSIA response (quoted above) — her answers to my interview questions on this occasion were minimalistic, providing at times only glimpses into her ongoing interests and passions. However, her later participation in the study was remarkably fruitful in helping me to understand how the use of self-data can offer new possibilities for concernful
involvement for learners — her reticence in this initial interview seems as though it may have been a consequence of her shyness, combined with the awkward medium of online video communication.

**Figure 4.** Sarah’s responses to the QSIA.

Prior to participating in this study, Sarah had been tracking her sleep using an app that she downloaded to her phone. She has been doing this for about a year, and has used the data to figure out how much sleep she “functions best on” (which, she has concluded, is around 9 hours of sleep each night). The app would prompt her to rate how she feels after she gets up in the morning, and superimposes this qualitative data on the number of hours of sleep she gets each night. This has allowed her to gain a basic familiarity with how her sleep affects her daily mood. She had also tracked her daily calorie consumption, also using an app on her phone, because — as she explained — she had wanted to maintain her weight. Besides generally keeping tabs on her spending (by looking at monthly spending totals), she had never tracked anything else about her self or her
activities. When asked how she thinks statistics might assist her in her existing self-tracking abilities, she mentioned that aggregating data (such as finding a monthly mean, or something similar) could be very helpful to her.

At this point in the interview, we explored together Sarah’s responses to the QSIA. She expressed little interest whatsoever in blood pressure, breathing, and phone usage; when asked about why she was not interested in tracking these aspects of her life, her responses were revealing (I neglected, for some reason, to ask her reasons for her similar disinterest in stair flights):

Blood pressure: “I don't see the significance in my life in tracking that, because I don't have high blood pressure, and I just think it would be kind of... not boring, but it wouldn't have any significance to me personally I guess.” (Sarah, initial interview, May 18, 2015, 00:28:13)

Breathing: “Probably the same reason. It's not something that interests me I guess.” (Sarah, initial interview, May 18, 2015, 00:28:38)

Phone usage: “I don't think that I use my phone too much, or too little, I think I’m fine, so I'd find it interesting if I had a problem with my phone, or was always on it or something like that, but I feel pretty comfortable with how much I use it, so again it's probably just the personal significance.” (Sarah, initial interview, May 18, 2015, 00:29:18)

A more detailed analysis of these responses is found in Chapter 6, but they each have a common thread: she does not have high blood pressure, does not have bad phone use habits, she does not have a problem breathing, and so these aspects of her life do not hold personal significance to her. This indicates that she has a preference for tracking aspects of her life where she sees room for improvement or feels like she has a problem; or, at the very least, has little interest in tracking aspects of her life where those things are not the case. In contrast, she expressed a lot of interest in tracking her mood, sleep, and steps. Her responses when asked why were a little bit more varied:
Mood: “I’ve been diagnosed with depression, because I had to come home early from my mission from an illness… So, it would just be interesting to track that, and I haven't really tried that before.” (Sarah, initial interview, May 18, 2015, 00:27:30)

Sleep: “Because I already do it, so it wouldn't be a big change in my normal schedule. I think that's the only reason that I can come up with right now.” (Sarah, initial interview, May 18, 2015, 00:26:12)

Steps: “Well a lot of people in my extended family use a Fitbit, but I have never used it, but I think it would be interesting to calculate how many steps I take a day, to see where I'm at — like what average.” (Sarah, initial interview, May 18, 2015, 00:29:53)

What is interesting here is that her reasons for tracking her mood clearly follow the pattern of her reasons for not tracking her blood pressure, breathing, and phone usage; in this case, she experiences mood problems, and wants to empirically document those experiences — which means that the ups and downs of her mood have a personal significance that the ups and downs of her blood pressure, breathing, and phone usage do not. Her difficulties with her mood imbued those ups and downs with personal significance. However, her reasons for wanting to track her sleep and her steps did not follow the same pattern; she wants to track her sleep for reasons of convince, that is, because she already tracks her sleep on a daily basis (although not using a Fitbit). And her reasons for wanting to track her steps seem at least partially social: she wants to participate in the rest of her family’s in use Fitbit device.

Following our conversation, Sarah expressed her plans to take measurements of her mood three times daily. In a follow-up email (22 May, 2015), for example, she stated, “I set the reminders for 9, 2, and 8 so it's spread out over the day.” Her actual readings look very different from this — there was only 1 day during the 75 days of her participation in the study in which she took three readings, only 4 days in which she took
2 readings, and only 19 days in which she took any reading at all. Her persistence in tracking her mood also seemed to decrease over time, as illustrated in Figure 5. One possible reason for her lack of persistence is that Sarah had set up the tracking app in such a way that taking readings was incredibly burdensome — or, rather, she neglected to set up the tracking app in such a way that would have dramatically simplified her measurements.

Table 7

<table>
<thead>
<tr>
<th>Choice</th>
<th>Stated Reason</th>
<th>Tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sleep</td>
<td>She already tracks her sleep.</td>
<td>Fitbit Flex</td>
</tr>
<tr>
<td>Mood</td>
<td>Diagnosed with depression. Has never tracked mood before. Would be interesting to track.</td>
<td>T2 Mood Tracker</td>
</tr>
<tr>
<td>Steps</td>
<td>Many people in her family have a Fitbit. Would be interesting to see daily average.</td>
<td>Fitbit Flex</td>
</tr>
</tbody>
</table>

The T2 Mood Tracker app has, on its default mood questionnaire, dozens of questions to respond to, measuring dozens of different mood dimensions. Users are expected to edit the default questionnaire by deleting questions until they had only a handful of dimensions that they were interested in. I had provided specific and detailed instructions to Sarah on how to do this, and had assumed from our communications that she had been successful (in response to my detailed instructions, she replied, “I've downloaded the app and I have it ready. … I added a category of my own.” 22 May, 2015). However, she had not removed any of the existing questions on the default questionnaire, and had only added new questions to it. Responding to the mood
questionnaire took her 5 minutes or more each time she did it. This lead to user fatigue, and thus a lack of persistence in taking continued measurements (illustrated in Figure 5). In contrast with her mood tracking, however, there were only 5 days in which Sarah lapsed in her tracking of her sleep patterns (all the same week), and only 2 days in which she lapsed in her tracking of her steps.

**Figure 5.** Sarah’s mood tracking over time.

**Data Exploration Meeting #1.** During the first data exploration meeting (which took place on 10 July, 2016) we used the Tableau data visualization software to visualize some of her mood data. A good 10-15 minutes of this meeting was spent formatting and cleaning her mood data, which she did not export for processing until the beginning of the meeting. This was a more complicated process than expected, because of the sheer number of dimensions that were included in the data. At her request, we included 10 dimensions in the mood data, which included (as they were labeled by the app) Content, Hopeful, Connected, Optimistic, Happy, Relaxed, Energetic, Loved, Safe, Calm. On each
of these dimensions, Sarah recorded her mood on a scale from 1-100 (but which was visually represented in the app as a scale from 1-10).

Sarah and I conversed about the complexities of data curation and how different software makes it easier or more difficult to transform and clean up data. I demonstrated how to clean up the mood data using R, which I then exported into a .csv file. Using that .csv file, we then made a histogram of her mood measurements in Tableau, with counts on the y-axis and mood score on the x-axis. We started with Happiness, which is a dimension prompted by the question, “On a scale from 1-100, how happy are you right now?” (responses were indicated using a sliding bar). We noticed that the histogram distribution was bimodal, with values clustering on the low end of the spectrum, and values clustering on the high end of the spectrum, with very few in between. Sarah teased that, from the data, it looks like she is “bipolar.” (An example of such a chart can be seen in Figure 6.)

Figure 6. The first data exploration meeting with Sarah.
A similar pattern was observed for each of her mood measures — a bimodal distribution was observed each and every time. This led to a series of humorous moments; as each histogram was created in Tableau (done by simply switching out the dimension variable in the Tableau interface and updating the chart), would show the exact same distribution shape, leaving us wondering if the chart had even updated at all. Each time, Sarah and I laughed a little bit more at how consistent the values were. Even dimensions that we would not expect to take a bimodal distribution seemed to do so nonetheless (such as energy level). Together, we speculated why this might be the case: I suggested that when she completes the questionnaires, she might place values in the extreme regions of the measure so as to better distinguish between the ups and the downs; perhaps, we discuss, we experience mood in more qualitative terms (good vs. bad), rather than quantitative terms. Neither of us was entirely sure how we would test this hypothesis.

These bimodal distributions provided a perfect demonstration of the central limit theorem, which she had recently learned about in her course. I demonstrated the central limit theorem using R. To do this, I wrote code that would sample her data, find the mean of the sample, and store than mean in an array; the code would then collect a new sample and do the same, as many times as we wished. We could change the size of the samples, and the number of samples, by changing the initial values used in the code. We could then plot the array (in which we stored the sample means) as a histogram. I was able to demonstrate that using this code that, regardless of the shape of the underlying data, the sampling distribution of the mean would be normally distributed, if the sample sizes were
large enough. This became particular clear as we compared the underlying bimodal
distribution with the normally curved sampling distribution of the mean, and observed
how the mean of the sampling distribution of the mean began to more exactly resemble
the underlying distribution mean, especially as we increased the number of samples or the
sample size.

![Histogram and sampling distribution](image)

*Figure 7.* Histogram and sampling distribution observed on 10 July, 2016.

We then mapped out Sarah's mood aggregated across the hours of the day,
starting with the happiness dimension. We observed that the values where consistently
the highest at around 11pm — and that they were substantially higher during that time. I
asked her why this might be the case. The following exchange took place:

192 Sara: Cause I’m usually happiest at night. That’s when me and my family are
193 playing games or watching movies is at night, and that’s what makes me happy.
194 [I replace the Happiness dimension with the Energetic dimension, and we refresh
195 the chart.]
196 Jeff: If we look at energetic, we see the exact same pattern.
197 Sara: [Laughs.] It’s kind of weird that I’m the most energetic at 11 at night, but…
198 but it makes sense.
199 Jeff: Is this what you expected?
Sara: I don’t know what I was expecting. (First data exploration meeting, July 16, 2015, 01:08:30)

I replaced the dimensions repeatedly, cycling through all of the dimensions of the mood data. Again, Sarah’s amusement escalated each time I refreshed the chart, each time revealing the exact same pattern for an additional mood dimension; on each of the mood dimensions, Sarah scored most desirably at around 11:00pm at night. Sarah did not know how to account for this trend, and wondered if her mood might correlate with other aspects of her data.

We then decided to create a similar histogram for her step data. I asked her what she thought the shape of the distribution would be, and she replied that she thought that it would be a lot more normally distributed, and a lot less bimodal than her mood was. At this point, I displayed the data, and her immediate response was, “Never mind…” The histogram is extremely skewed towards zero (demonstrated in Figure 7). At this point, I explained that the data was skewed because we are looking at 15-minute intervals, and that most of us sleep or sit for large portions of the day. She then asked if the distribution would be normal if we looked at daily step totals. Using Tableau, however, we were unable figure out how to display a histogram using daily step totals; we did imagine what it would look like, however, by looking at her daily means. I then demonstrated the central limit theorem again, using the highly skewed step data. At this point, I then asked Sarah what more she wants to know about her steps, and she replied that she wants to know which day she walks the most. We displayed the daily means (aggregated by weekday) in Tableau, and discovered that she walks the most on Fridays.
We then turned our attention to sleep, and looked at sleep duration. This is again a bimodal distribution — Sarah either sleeps a lot, or sleeps a little, oscillating somewhere between 350 minutes and 600 minutes a night. Sarah hypothesized that she sleeps the most on Sunday — but when we displayed the daily means (aggregated by day of the week), this did not appear to be the case. We explored the data in a little bit more detail, displaying all Sundays in the dataset, and discovered an outlier that has a disproportionate effect on the mean — and after removing the outlying variable, it did appear as though Sarah sleeps more on Sundays. We also discussed the nature of how the data was collected, and speculated as to whether the Fitbit is counting sleep the previous evening, or sleep starting on that evening. We also observed substantial variation in her recorded restless time during the night — she hypothesized that the high values (which were more frequent earlier in her data) were the result of a new puppy she had brought home, which grew less demanding of her during the night as it grew older. She also hypothesized that

**Figure 8.** Histogram of step data observed by Sarah.
the lowest values (close to zero) are due to a few days in which her Fitbit fell off during the night.

**Data Exploration Meeting #2.** The second data exploration meeting took place on the morning of August 5, 2016; due to multiple reschedulings, the meeting could not be convened as early in the semester as either of us had hoped. At this point in the semester, Sarah admitted to being deeply discouraged with the statistics course, a theme that we will discuss in great detail later. She explained that she felt that hypothesis testing — which she had been learning about for the past two or three weeks — might be the most useful thing she has learned so far, but that she could not think of an application for it in her own life. As had been planned, hypothesis testing became the topic for the meeting.

I asked her what questions she might want to ask about her steps, her mood, or her sleep, and she stated that she does not know. So I presented to her several options that I had prepared in advance: we could ask whether she walks more on weekends or weekdays, or during the mornings or the evenings, for example. Sarah decided that she was interested in knowing whether she walks more on weekends or weekdays, because she had a suspicion that she walks more on Sundays than the rest of the week; but, she said, this suspicion could be untrue, considering her observations during the last data exploration meeting that she sleeps more on Sundays than on other days. At this point, we had a conversation about whether or not the data she has collected could be considered a random sample, and how that affects our analysis; I explained that, for our analysis to be valid, we would need a truly random sample, and that we would therefore
need to *pretend* that her sample is randomly sampled from the larger population (her walking habits generally), in order to demonstrate hypothesis testing.

We used Excel to perform a t-test on her step data, comparing weekends and weekdays. Much of the remainder of the meeting involved a discussion of the technical skills required to perform statistical analyses in Excel; up to this point in her course, Sarah had performed all of her analyses using a TI-83 calculator. All of the data sets that she has had to use so far have been small enough that she could easily input the values into the calculator. The data set that includes her step data was, therefore, substantially larger (by several orders of magnitude) than anything she had worked with before. Sarah completed most of the calculations herself, with some tutorial help from me. To accelerate some of the trickier and more time consuming parts of the analysis, I at times demonstrated techniques in Excel to automate some of what she was trying to do. She was glad to learn new and more efficient ways to perform calculations that would otherwise be time consuming on her calculator.

We first created a column in the spreadsheet that displayed whether a measurement took place on a weekend or a weekday; we then calculated the mean of each group. At this point, Sarah’s posture and demeanor changed remarkably. Consider the following exchange, in which I read off the results of her calculations:

202 Jeff: So, an average of 5870 steps on weekdays, and 5619 steps on weekends.
203 How does this compare with your expectations, that you mentioned earlier?
204 Sara: It’s opposite. But it’s pretty close. 200 steps isn’t that much different… but we can use a hypothesis test to see if it’s significant! [There’s an excitement and realization in Sarah’s voice and her gestures, as if she just figured out a riddle.]
207 Jeff: Exactly.
It is interesting to note at this point that Sarah’s response here reflects a similar intuition that learners in previous studies related to self-data have exhibited — in an earlier study involving elementary-aged learners, learners who were comparing different physical activities also concluded that a small difference in means was unlikely to be consequential, based on intuitions about the magnitude of a difference in means that would be needed to draw conclusions about the underlying phenomenon (Lee, et al., 2015). At this point, I demonstrated how to conduct a t-test in Excel, using both a manual formula, and also Excel’s built in formula. We noted that the difference in means had a $p$ value of .26, and we discussed what this means (which is, I explained to her, that if the two population means were truly the same, we might expect to observe this difference of means between two randomly drawn samples of similar size around a quarter of the time). Sarah rightly concluded from this that we cannot know for certain, from the data that we have, that the observed difference in means between her weekend steps and her weekdays steps was not due to random variation.

At this point, we turned our attention to her sleep data, and Sarah calculated the means for her weekend sleep duration and her weekday sleep duration. The means were barely over 6 minutes apart (502.4 minutes for weekdays, and 508.9 minutes for weekends) — which she notes to be a comparatively small difference, especially considering the standard deviations for the two groups (100 minutes for weekdays, and 125 for weekends). This time, Sarah immediately moves to compute the $p$ value, knowing
that comparing the means alone would be insufficient to draw any conclusions. The p value turned out to be .411, and Sarah concluded (again) that we could not reject the null hypothesis, which she correctly determines to be that the means are equal. At this point, she was surprised, because of the substantial difference she recalled observing in her Sunday sleep patterns while exploring her data during our previous meeting; we returned to Tableau and visualized her sleep patterns again. Since our previous meeting, the difference between her Sundays’ sleep and the rest of the week seemed to have all but disappeared.

Sarah then asked whether she walks more during afternoons than in mornings. Together, we defined 8am-12pm as morning, and 12pm-5pm as afternoon. The metric we used was steps per quarter hour. At this point, Sarah was starting to wonder what else she has learned in her class she could use to analyze her data; for example, without any prompting from me, she asked if it is theoretically possible to compare morning, afternoon, and evening using ANOVA (we did not conduct this analysis, however). We calculated the means for the two groups, and determined that there is a difference in means of 40 steps per quarter hour. The standard deviations of the two groups, however, were also large (135 and 173). This time, however, the t-test revealed a statistically significant difference, with a p-value of 2.68x10^-12. Sarah’s response was, “So there’s like noooooo chance [that this could be due to random variation]” (Sarah, third data exploration meeting, August 5, 2015, 00:53:15). We performed two more hypothesis tests: one to see if she is happier on weekdays or weekends, and one to see if she is happier in the evenings than in the mornings. In neither case were the results statistically
significant. At this point, we were drawing to the close of the meeting, and the following exchange occurred:

Jeff: So we found one statistically significant difference, and that was walking in the mornings and afternoons. Do you have any more questions?

Sara: No. That was cool.

Jeff: Why was that cool?

Sara: Cause I actually got to use what I learned.

Jeff: Had you not been able to use it before?

Sara: No, not for this class. (Second data exploration meeting, August 5, 2015, 01:02:10)

At this point, Sarah decided that she does not want to wait to meet again; she wanted to complete her homework for the week (related to correlation), and return that afternoon to do more analysis. This is in part to save her the time of having to return to Logan for another interview, but also in part because she was excited about what she was doing during our meetings (implied by her initial decision to meet another day, and then her subsequent decision — after the first meeting — to return later that day, coupled with her stated excitement about the activities of the first meeting).

Data Exploration Meeting #3. The third data exploration meeting took place on the afternoon of August 5, 2016. When Sarah left the previous meeting, she spent the remainder of the morning and the first part of the afternoon completing her weekly homework and studying correlation. At the very beginning of the meeting, I asked Sarah how her studies that day went, and she replied, “I actually understood it. … It didn’t take me hours and hours to do the homework like it normally does. It was good.” This was in part because of the Excel skills that she learned during the previous meeting; she
explained, “I used Excel on our homework instead of using the calculator, and it was a lot easier” (Third data exploration meeting, August 5, 2015, 00:02:20). She also stated that, after she left the meeting, she called her mother and told her about what she was learning while exploring her data. She said, “I called my mom and was like, ‘Mom, guess what? I understand stuff!’” (Third data exploration meeting, August 5, 2015, 00:02:05) At this point, we discussed how correlation might be used to examine her own data. The following exchange took place:

219 Sara: [W]e can see with this data if the steps or sleep or mood is correlated.

220 Jeff: Do you think it is?

221 Sara: Yes.

222 Jeff: Why is that?

223 Sara: With my steps and my sleep, it would be because… well, if I go running one day I take more steps, and then I would probably be more tired and sleep more, or sleep better. (Third data exploration meeting, August 5, 2015, 00:05:20)

We then explored whether there is a correlation between her sleep duration and daily steps. During this meeting, Sarah took much more ownership of the analysis during this meeting than she has during previous meetings. This is part because she had just completed her homework for the week, which was related to correlation, so the procedures were fresh on her mind. The correlation coefficient was determined to be $r = -0.24$. This indicated, to Sarah’s surprise, that the more sleep she got, the fewer steps she took, and vice versa; simultaneously, Sarah stated, “I was expecting it to be more correlated than it is,” i.e., whether negative or positive, she was expecting a greater connection between her sleep and her steps than was observed in the data (Third data exploration meeting, August 5, 2015, 00:27:50). We subsequently determined that there
is no connection between her mood data and her sleep data; but there did seem to be a
moderate, negative correlation between her mood and her sleep duration. We discussed
the implications of this:

Sara: So, negatively correlated?

Jeff: Which means, that the happier you are, the less sleep you get that night.

Sara: I should stop being happy I guess.

Jeff: It’s not small, but it’s not large either. It’s a modest correlation. A full
quarter of the variance in how much you sleep might be accounted for by how
happy you were that day. …

Sara: Yeah, that’s the opposite of what I thought. It should be…

Jeff: Yeah, and this says that the more happy you are, the less you’ll sleep. Is it
because you are up later at night?

Sara: Yeah, maybe it’s because I’m like, “Yay! I’m so happy I’m not going to
sleep at all.” (Third data exploration meeting, August 5, 2015, 00:38:30)

We also discovered that the more relaxed Sarah reported being on a given day, the
less restless time was recorded in her sleep the following night. Sarah had no reaction to
this discovery, but was interested in correlating how energetic she was and her daily step
totals. The following conversation took place:

Sara: I think there will be a positive correlation — the more energetic, the more
steps I take.

[Jeff presses enter, and the calculation is performed, revealing a small, negative
correlation of r = -.20]

Sara: [Laughs] Why? Why is it negative? Cause that means that the more
energetic I am…

Jeff: …the less steps you take. Maybe taking steps drains energy? [Sarah laughs.]
The more energetic you are, the fewer steps you take, if there’s even a correlation
at all.
Sara: [Gestures with her hands, shakes her head incredulously.] Right. That’s just weird. [Laughs.] (Third data exploration meeting, August 5, 2015, 00:45:50)

At this point, we were nearing the end of our meeting. We ran a few more correlations, with different mood measures, between steps and sleep; in none of the remaining calculations did we find a correlation. Sarah laughed each time, and a subtext of her amusement is that each absent correlation made the correlations we did find, in her mind, more credible — despite the fact that they contradicted her expectations. After this, the meeting came to an end.

Practical Considerations when Collecting Self-data

While a number of the participants chose to track other elements of their life, such as their computer usage or their mood, every single one of them availed themselves of the opportunity to borrow and use a Fitbit as part of the study. Six of the seven participants chose to track their steps, five of them chose to track their sleep, and three of them chose to track their heart rate. This does not mean that, for those who tracked their steps, steps were their first choice — the three that chose to track their heart rate each made heart rate their first choice, but because the Fitbit tracked steps as well, they made steps a secondary object of inquiry out of convenience. Only one participant (Peter) did not track steps. He used his Fitbit to track his sleep, and thus wore it only at night.

Table 9 lists the results of the QSIA for each participant in the study. A “5” represents great interest, and a “0” represents no interest. It is important to note that their responses to the QSIA did not necessarily reflect what they chose to track during their initial interview, nor did it reflect the preferences that were revealed through further
discussion of their interests during the initial interview. Peter, for example, responded with high values on every item on the QSIA, but during the initial interview, he articulated preferences that were much more varied and nuanced than were reflected in his responses. Something similar was true for each of the other participants — while their responses on the QSIA reflected to some degree their varied interests, those interests occasionally shifted when they were able to ask more information about how the data would be collected, what would be required of them, and what information would be made available to them through tracking, etc.

Table 8
A List of Participants’ Responses on the QSIA.

<table>
<thead>
<tr>
<th></th>
<th>Steps</th>
<th>Heart rate</th>
<th>Breathing</th>
<th>Sleep</th>
<th>Blood pressure</th>
<th>Stair flights</th>
<th>Mood</th>
<th>Phone usage</th>
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<td>Brian</td>
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<td>Sarah</td>
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<td>Kristen</td>
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<td>Chris</td>
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We can see, for example, that none of the participants put anything less than a “3” for steps or computer usage, and none of them put anything less than a “4” for sleep. While the sample sizes here are small, these results hint that steps, sleep, and computer usage — of the options that I made available — might be the most broadly interesting or engagement to learners. Heart rate seemed like it followed those options, with all participants rating it a “3” or above except one (Brian). Conversely, it seems that blood
pressure, stair flights, and breathing and much lower appeal to the participants (broadly speaking).

My interviews with the participants, as well as the data exploration meetings, revealed useful, practical considerations to take into account when using self-data in a statistics learning environment. These considerations seemed separate from the issue of “mattering” (as defined in the context of this study), as they were less related to the project of involving learners in statistical inquiry with an invested concern similar to that of disciplinary professionals. The considerations outlined below may inform the types of technologies that statistics instructors make available to learners, the instructions they give to learners, and other strategies for the successful implementation of a statistics curriculum that makes use of self-data as a way of inviting learners to care about data analysis (and thereby involve them in statistical inquiry as a tool for exploring their world).

Table 9
A List of Participants’ Data Collection Choices and Tools

<table>
<thead>
<tr>
<th>Participant</th>
<th>Tracking choices</th>
<th>Tracking tools</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greg</td>
<td>Steps, heart rate, sleep</td>
<td>Fitbit Charge HR</td>
</tr>
<tr>
<td>Brian</td>
<td>Steps, sleep, computer usage</td>
<td>Fitbit Flex, RescueTime</td>
</tr>
<tr>
<td>Sarah</td>
<td>Steps, sleep, mood</td>
<td>Fitbit One</td>
</tr>
<tr>
<td>Kristen</td>
<td>Steps, heart rate, sleep, computer usage</td>
<td>Fitbit Charge HR, RescueTime</td>
</tr>
<tr>
<td>Chris</td>
<td>Steps, sleep, phone usage</td>
<td>Fitbit Flex, Moment</td>
</tr>
<tr>
<td>Britney</td>
<td>Steps, heart rate, sleep</td>
<td>Fitbit Charge HR</td>
</tr>
<tr>
<td>Peter</td>
<td>Sleep, computer usage</td>
<td>Fitbit Flex, RescueTime</td>
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</tbody>
</table>
Wearable devices seemed to intrigue participants in the study.

Put in other terms, each and every learner chose to use wearable technologies to collect data about themselves when the option was presented to them, even when they had a number of other options available to them. Whether this is due to the conspicuous consumerism associated with wearing a Fitbit, the novelty and popular appeal of this specific device, or just that the data collected by the Fitbit is innately more interesting to learners than the other options (such as weight, blood pressure, mood, etc.), we cannot say for certain with the data at hand. Prior research has indicated that users are often enthusiastic in their adoption of the Fitbit as an activity tracker (Jochen Meyer & Hein, 2013), but this enthusiasm has not (to our knowledge) been compared with other devices.

But this does lead to an important observation: when using self-data to help make statistics more relevant to learners, wearable technologies may very well be the measurement instrument of choice. However, the choices of the participants in this study may have been entirely due to their desire to take advantage of my offer to loan them a wearable consumer device that they find intriguing, but have no plans of purchasing on their own. Kristen, for example, expressed this very thing on multiple occasions. For example, during the initial interview, she explained:

> [It] was nice to hear that I would have the opportunity to use these things that I probably would just never pay the money for, and therefore never know how it would affect my life or not. And so for this, [motions to Fitbit] it's like a trial period where I get to try it out and fiddle with it, and what not, and I can decide later if I want one or not. Because I've thought about buying one before (Kristen, initial interview, May 7, 2015, 00:43:31).

Kristen stated explicitly here that her interest in using the Fitbit was grounded at least partially in the ability to use for free a device that is normally fairly expensive for
the average consumer, and so she wanted to take advantage of the opportunity to “try out” the device. While I was unable to find explicit evidence of this in the interviews and statements of other participants, I suspect that similar motivations factored into their decisions as well.

**Participants in the study preferred automatic data collection.**

One interesting observation is that, when given a choice, participants preferred not to engage in tracking that required them to actively take regular measurements; that is, they were far more willing to engage in activity tracking that was automated, and took place without their active cooperation. Britney, for example, expressed interest in better understanding her mood, but expressed much less interest in actually tracking her mood. She explained, “I care. I don't want to just track my mood, like ‘Oh, every 15 minutes I'm feeling happy, or I'm feeling happy’” (Initial interview, May 13, 2015, 00:27:14).

Only one participant in the study, Sarah, tracked her mood (which, besides blood pressure — which no one who completed the study chose to track — was the only data tracking that required the active cooperation of the user). Her less successful experience tracking her mood is described above (on page 100). Due to user fatigue, which resulted in a lack of persistence in taking continued measurements, Sarah obtained (on average) less than 2 measurements each week, as opposed to the 3 measurements each day that she had intended to obtain. Sarah’s experiences demonstrate that automated data collection, such as the data collection performed using a Fitbit device, may be more likely to yield large amounts of data for learners to analyze.
This is, in fact, an observation that is interesting to the larger questions of this study. Disciplinary professionals who engage in data collection often find the need to actively and regularly collect samples and take measurements; the type of disciplinary investment we hope to recreate in a statistics learning environment would (we hope) motivate learners to collect data even when it is inconvenient. That this was not the case for at least one learner in this study is potentially revealing: the use of self-data may recreate some elements of that disciplinary investment, but perhaps not always to the same degree.

**Participants wanted data to be readily accessible.**

Learners were more successful in engaging with their data when they could view the data in real time, without extra effort on their part. Brian, for example, chose to track his computer usage, which was done using the RescueTime app installed on his computer. To view the results of his computer tracking, he needed to log into RescueTime online. He did not do this at any point during the study. During the final interview, he explained (comments here are consolidated from multiple points in the interview):

254 I didn't know how to look [computer usage] up because I forgot the password …  
255 But for the steps, mostly because it was on the phone, I could track it really easily.  
256 … With steps it was just a button to see where you were. … I got really interested  
257 in the tracking, especially the steps. Not much the sleep or the computers, but the  
258 steps. That might just be because it was there. I don't know if it was anything  
259 about steps in particular, or if I had any easily available tracker on my wrist, I  
260 might just look at it a lot. (Brian, final interview, August 21, 2015, 00:44:25).

In this example, Brian demonstrates that accessibility may be an important consideration when choosing devices and applications to use for self-data collection in a
statistics learning context. Another example can be found in Kristen’s interactions with me during the first data exploration meeting. At the beginning of the meeting, I asked Kristen how the data tracking was going for her. She immediately mentioned that it was really interesting to see her heart rate and her steps. She said, “Sometimes I’ll just be sitting, doing nothing, and my heart rate will be 90 or something, or 100 something. And I’m like, ‘Why?’” (First data exploration meeting, June 5, 2015, 00:02:10) She explained that this has driven home for her that she needs to strengthen her heart by doing more cardio exercise. She also mentioned that is was interesting to see how much she did or did not sleep at night. In multiple instances during this conversation, she pointed to her wrist, and to her smart phone. At one instance, she looked at her wrist, mimicking what she would do when “checking her heart rate.”

What is interesting is that, while I offered her multiple opportunities to bring it up, not once did she mention or volunteer any information about her experiences tracking her computer usage. It was almost as if she had forgotten that she was tracking it at all. In fact, her computer usage data was address in data exploration meetings only when I brought it up to her; she did not initiate conversation about it with me. The other aspects of her life that she was track — her steps, her heart rate, and her sleep patterns — were all tracked on her Fitbit device, which synced with her smart phone. This allowed her to receive real-time continuous feedback on her steps, her heart rate, and her sleep by merely looking at the device on her wrist, or looking at the app on her phone, which she kept with her on a daily basis. In contrast, her computer usage data was accessible only by logging into an online app. In later conversation, she revealed, “I feel like I don’t use
my computer as much. Because usually I’m like running around all over the place. So I’ve been using the internet on my phone” (Kristen, first data exploration meeting, June 5, 2015, 00:05:45). In addition, Kristen remarked that she does not enjoy browsing the Internet on her phone because of the small screen size. These factors combined to make it less likely that Kristen would actually log into RescueTime to keep tabs on her data outside of data exploration meetings.

This indicates to me that the means of tracking — and its affordances for providing ongoing, conveniently accessible feedback to users — may play a significant role in whether or not the use of self-data can plug into the ongoing concerns of the learner. Devices like the Fitbit allow the learner to access and view the data in real-time. Kristen remarked, for example, that she would look at her heart rate while she was engaging in sedentary activities, and be surprised at how high it was. This sort of “immediate availability” of the data allowed Kristen to engage with the data in the moments that she found herself concerned about or interested her heart rate, rather than after the fact. In contrast, while the RescueTime app does have a mobile version that can be installed on the smartphone, we simply did not install the app on Kristen’s device, in part because we were tracking her computer usage, not her phone usage.

**Participants wished that they had a record of their daily activities.**

Another consideration that was revealed in this study is that many learners simply do not remember all the things that they do each day — and therefore, while the data is about themselves (and thus situates them as experts with respect to the data, in a way that they would not be if the data were contrived or handed to them by an instructor), they
may not be able to remember the life events and experiences that give shape to the data. For example, in the final interview, I asked Kristen what she wishes she had done differently during the study. Her response mirrors the response of other participants (more on that shortly): she replied that she wishes she had kept a journal. Consider this exchange, in which I asked her about her computer usage tracking:

Jeff: What do you think would have been your computer usage more interesting to track?

Kristen: [Pause.] Maybe if I had a journal to go along with it, like not just seeing that I spent a lot of time on the computer this day and not very much that day. Just things like… Really short, probably like… It wouldn't really need to be long, but just shortly what am I thinking about that day, am I procrastinating something, or on this day, why did I not get on the computer? What was I doing that day? And this day, you know all that productivity time, how much of the time on productivity led to wasting time, stuff like that. (Kristen, final interview, June 24, 2015, 00:22:59)

Later, she continued this theme, stating again that the reason for keeping a journal during data tracking would be so that she could better understand and interpret the ups and downs of her data weeks after the fact:

Maybe just tiny little journals and stuff. Maybe not even call it that. If from the beginning I had been asked to also keep a journal, it would have seemed more… more work, but just jot down two sentences about what you do in the day, just so that you can... Because there were a lot of times where we were looking at the data and I was like, “What the heck, I don't even know what I did that day.” I wanted to know like what might have caused it, or what that might have caused. (Kristen, final interview, June 24, 2015, 00:53:39)

Like Kristen, Greg also felt that journaling would help him engage in better sense-making of the data. He explained that this was so that he could better understand the behavioral covariates of the ups and downs of his data:

I think it might've helped me to understand some of the different things that we recorded, like maybe with my steps, maybe writing down on a log. So for, you know, August 21st I walked so many steps because I did this activity. So it's like
I'm getting a better insight into why I was getting more steps, and why my heart rate might've been a little bit higher that day, because I was expending more energy. So keeping a log I think would've helped. … I think it gives you more insight. I think you can see more into it. But then to be able to go back and look at it, you see more correlation, and see what influences things more. (Greg, final interview, August 21, 2015, 00:36:45)

In this comment (from the final interview), Greg explains that keeping a journal would have provided qualitative factors that he could use to better make sense of his tracked data. The challenge with this practical consideration is that it directly contradicts the earlier consideration: that data-tracking may be better when it is automated (and does not require the ongoing cooperation of the learner). However, two separate participants in the study specifically mentioned that they wished they had done this, and that this would have helped them better leverage their own expertise of the data when engaging in interpretations of their data and the results of their analysis.
This section will explore the findings of this study in relation to the research question, “Under what conditions do the use of self-data (and the questions asked about the data) matter to learners?” Again, it is important to situate this question in the broader argument of this study: we want self-data — and the questions that learners ask about the self-data — to matter to learners because we hope that this will help learners become invested in the statistical analyses they perform to answer those questions. This is important because without this investment, learners may be more likely to see the statistical practices they are learning as mere classroom exercises, as tools for passing a class, rather than instruments of inquiry that they can use to illuminate their world and advance ongoing life projects (which is how a disciplinary professional, such as a medical researcher, might view statistics).

I would like to note that these findings involve a complex interplay between learner’s varied ongoing concerns and interests, their participation in the statistics course, their participation in the study, the types of data they chose to collect, and the questions that were readily answerable using the data they collected and the statistical tools available to them. In short, it is difficult to summarize these findings without articulating in some detail the various narratives of each individual learner, and how the use of self-data tapped into their existing concerns and interests (and, in some cases, how the use of self-data opened up new possibilities for concern and interest). For this reason, there will
be significant overlap between this section and the following section, in which I explore in more detail the narratives of a couple of the participants in the study.

In doing so, I will deconstruct and challenge the assumption that self-data matters to learners simply by virtue of it being about the self. That is to say, learners were generally not engaged in the analysis because of some vain, inherent interest in the self; there were plenty of contexts in which the data and questions were uninteresting to learners, while still being about the self. However, the hope, again, is the mimic in some ways the disciplinary investment or passion that learners might develop if they were addressing concerns or interests they might have in a professional context (e.g., a graduate student engaging in academic research, or a medical professional trying to test vaccines, etc.). These professional concerns or interests rarely deal with the self as such, and so it would in fact be less fruitful if self-data engaged learners solely out of a sense of personal vanity, and for none of the reasons that disciplinary professionals are invested in their data analyses.

But this is not to say that “being about the self” did not matter at all — in fact, it mattered a great deal. By analyzing the experiences of learners in this study, I found that being about the self did provide context for learners to be familiar with the data and its real world referents, and for the data to “plug into” and address existing concerns and interests of learners — and in ways that mimicked (in at least a rudimentary sense) the kind of disciplinary investment that professionals might have with their research questions and data. In the process, I observed a number of “themes” that hinted at some conditions necessary for this to happen. As I said earlier, being “about the self” was not
itself sufficient to make data analyses matter to learners, but other contributing factors — made possible in part by the fact that the data was about the self — helped learners to develop this invested engagement with the data and their research questions.

**Theme 1: Learners cared more when they could form expectations of the data.**

Because the data was about the self, learners were intimately familiar with the data — and their referents in their personal lives and activities — in a way they might not have been were the data provided by the instructor, or had the data been contrived for the purposes of instruction. This made it possible for learners to form expectations about what the data would show. Whether these expectations were confirmed or contradicted by the data was almost inconsequential; the ability to form such expectations, however, seemed to be a strong, contributing condition to “mattering.” If they are unable to form any expectations at all, they were less likely to care about the results of the analysis. This is in part a function of their familiarity with whatever aspect of their life is being tracked, and also in part the ability to make intuitive guesses — right or wrong — about what the results of their analysis would be.

I will argue that being able to make informed hypotheses, grounded in experience (whether personal or professional), may in fact be a vital part of seeing data analysis as an instrument of inquiry rather than as a mere classroom exercise. This theme was developed in part as I found many instances in which learners cared about the results of the data analysis precisely because it contradicted their expectations, as well as many instances in which learners cared about the results of the data analysis because it confirmed their expectations. The common factor, however, was that they had
expectations in the first place. Conversely, when learners were not able to form any expectations of the data, they were less likely to be able to ask meaningful questions about the data, or to care about the answers to analyses they performed.

**External benchmarks can help learners form expectations.** This theme may have in fact influenced the kinds of data that learners chose to collect. Most participants decided, for example, to measure their steps, sleep patterns, or heart rate. *None* of the participants expressed any desire to track their breathing. While we will discuss this in more detail later, I argue that commonly known and highly publicized external benchmarks can help inform the intuitions of the learner, which augments their ability to form expectations of the data. For example, if it is publicized that 10,000 daily steps is a benchmark for an active life (which is the benchmark used by most Fitbit activity trackers), an individual has a better basis for forming an expectations of his or her own data. An individual with a sedentary lifestyle might be able to guess (rightly or wrongly) that his averages own daily step averages are far below 10,000 (e.g., around 2,000 or 3,000).

Conversely, a learner has no such readily available or widely known external benchmark to use when forming expectations of their breathing rate; while there may be known averages and benchmarks against which medical professionals can evaluate someone’s breathing, these are not publicized in the same manner that Fitbit’s daily goal of 10,000 steps is publicized. This makes it much more difficult for learners to make intuitive guesses about what breathing data collected from, say, a Spire device might look like, and also more difficult to form meaningful, statistical questions to ask of the data.
What this means, then, is that the data — and the potential questions one might ask about the data — matter less to the learner.

This does not mean, however, that learners in that situation cannot ask relative questions for which they can form intuitions (e.g., someone with no knowledge of the 10,000 step benchmark might still find meaning in the question, “Do I walk more on sunny days than on rainy days?”). However, if they have no intuitive basis for forming even hypotheses related to relative values (e.g., “Do I breathe faster on sunny days than on rainy days?”), they may have a hard time finding themselves caring about the question. In addition, this also means that when analyses are able to either contradict or confirm a learner’s intuitions, learners are more likely to care about the results. This theme was observed in experiences of each of the participants in the study — all of them, at some point or another, made comments that hinted that the ability to form expectations of the data played a significant role in the way that the data analyses that they performed mattered to them. I will share three examples that illustrate this theme.

**Example #1:** At the beginning of the study, Chris chose to track (among other things) his sleep habits and his phone usage. During the third data exploration meeting, Chris explored the possibility of a correlation between the two. He was interested in seeing if using his phone more was associated with poor sleep habits; that is, if days with higher phone usage minutes were associated with nights with fewer minutes asleep. After performing the analysis, we did not find any evidence that there was such a correlation. During the final interview, I asked him whether this was significant to him, and he replied:
Personally, I thought if we looked at the sleep times [e.g., bed time and wake time] it would be different [e.g., significant results]. But, for sleep duration, I thought... I usually stay up late on my phone, just like, playing games and wasting time. I believed it would affect the sleep duration more, but I guess I just slept in the next day, and that kind of made up for that. But as far as the time of going to sleep and waking up I think that would be, that there would be a higher correlation with phone usage. (Chris, final interview, June 24, 2015, 00:32:26)

In this statement, three things happened: (1) Chris expressed that he had formed expectations of the data, based on his personal experiences (lines 268-270). He believed that his sleep habits would be associated with his phone usage. (2) Chris noted that those expectations were contradicted (or at least disappointed) by the data. He did not find the correlation that he was expecting (lines 267-268). (3) Chris continued to formulate questions and generate hypotheses about the data that were informed by his familiarity with his personal life (in lines 270-271, he hints at a further question, and in lines 271-272, he formulates an additional hypothesis). Note further that Chris, in this example, is seeing correlation as revealing a relationship between real world activities, and that Chris formed real-world hypotheses, grounded in personal experience, to test using correlation.

In other words, the practice of calculating a correlation is being disclosed to Chris as more than a classroom exercise, but as tool that he can use to confirm or disconfirm expectations he has of the world. Chris engaged here in several practices that are common to disciplinary professionals who engage in statistical analysis: (1) they form expectations of the data based on their disciplinary experiences and prior research, and use that to form hypotheses and ask questions; (2) they test those hypotheses using statistical analysis; and (3) they ask further questions and formulate further hypotheses.
based on their results. In the process, *correlation* is being used by Chris as an instrument for advancing this cycle of inquiry. This process is grounded at least partly in Chris’s ability to form expectations of the data, something made possible in this case by the fact that the data references his own personal life and activities.

**Example #2.** Peter also chose to track his sleep at the beginning of the study, as well as his computer usage. During the first data exploration meeting, we calculated his mean sleep duration, as well as the standard deviation of his sleep duration. During the final interview, I asked Peter about his experience doing this. Peter remarked, “[I]t was also really interesting to see how long I slept. Cuz I thought I only slept 8 hours, but it seemed like it almost averaged out more to a high 8, to almost 9, hours of sleep a night” (Peter, final interview, June 24, 2015, 00:13:54). First, note that Peter expressed great interest in the question — this interest was demonstrated during the first data exploration meeting in the way Peter engaged with the data analysis. For example, Peter insisted on accounting for any anomalies in his sleep data – trying to figure out (by pulling out his computer and exploring his calendar and course syllabi) precisely what might have contributed to those anomalies. Second, note that Peter found the results of the data analysis to matter to him at least in part because the empirical data contradicted his intuitive expectations. This level of interest in the data seems to be fueled by his familiarity with his personal activities, which allowed him to form expectations of the data.

**Example #3.** The third example also comes from Peter’s experiences. Peter’s intimate familiarity with his personal life and activities also allowed him to form
expectations of his computer usage data, in ways that invited him to similarly care about analysis questions related to his computer usage. RescueTime classifies hours spent on the computer as “productive” and “unproductive” based on the applications being used and the type of websites being visited. During the second data exploration meeting, we asked whether Peter’s “productive” computer usage differed between weekends and weekdays. As before, Peter’s expectations were also contradicted by the data, but this time, instead of adjusting his expectations, Peter expressed a strong disagreement with the data. During the final interview, Peter explained:

> I guess I have sour feelings towards the productive/unproductive because I didn't feel like it was efficient. … I just remember, certain days I know my schedule really well, and when I was doing certain things that were productive, like homework, or I was being tutored on the computer, or I was doing specific things that were related to school, those days were all tracked as unproductive. (Final interview, June 24, 2015, 00:24:19)

In this comment, Peter explained that he did not trust the results of his analysis because he did not trust the way RescueTime classified his hours as “productive” and “unproductive.” This distrust was rooted in his own personal familiarity with his daily activities, and his belief that the data contradicts the expectations he formed of his data based on his personal experience. Even though Peter was being dismissive of the analysis results that related to productive vs. unproductive time, he demonstrated the ability to form expectations of what the data would show.

It was this ability to form expectations — and the fact that the expectations were based on his familiarity with his own life activities — that allowed him to critically examine the data and analysis results. Even though Peter disagreed with the results of the analysis, he cared about those results enough to challenge them, and to try and reconcile
what the data showed with what he personally recollected about his activities — an endeavor that led him to conclude that RescueTime, as an app, was in error in the ways it classified computer usage. In this case, then, his personal familiarity contributed to his ability to invest in the results of the analysis, and to critically evaluate those results with the context of broader life experiences.

Example #4. Finally, this theme can be illustrated using a negative example from Kristen’s experiences — not with self-data, but with the data that she used in the statistics course. During the final interview, I asked her about the data sets she used in course (during her homework or class projects, for example). In response, she described some of those data sets (quotations are abbreviated to highlight relevant parts):

Kristen: There was a second data set given to us about hot dogs, calories, and stuff. And like, here's all the tables, and I can put it R, and analyze it. The only interest that comes from that is if you care about the differences between hotdogs, and you're like, “Oh, I should buy different hot dogs.” And even then you don't know where they sampled from, so you don't know if that's actually applicable to your actual life. … Otherwise, the only way you can get interested in it is if you say, "I have to think about this because I have to do the work.” You start thinking about it not because you are actually interested in it. …

Jeff: So the questions you are asking about the data, how much do those questions matter to you?

Kristen: Nuh, not at all. I mean if they didn't match up with what I expected, I'd be like, “What?”

Jeff: [Jokingly.] Like if the hotdogs are more healthy than the broccoli?

Kristen: Yeah, like, “Hey hold on, now I care.” But otherwise, it's just like, “Oh, this is significant, oh, this is not,” [said in a routine, mundane way] and sometimes it's like, "Ok, that makes sense," and you just move on with your life.

(Final interview, June 24, 2015, 00:31:59 - 00:33:54)

There are many notable features of this exchange, but what is significant for now is that Kristen had no idea what brands of hotdogs were even sampled in the data, or if
the data were even based on real-world samples in the first place (see lines 282-283).

While Kristen may eat hotdogs in her personal life, without knowing what brands were sampled in the data, there was simply no basis for her to for form any expectations about the results of her analysis of relative calorie contents of the hotdogs, much less have those expectations confirmed or contradicted. In fact, I might argue that, when simply looking at two brands of hotdogs (in a grocery store, for example), we usually use many neighboring cues to make informed guesses about their nutritional content (such as the kind of meat, the size, or the price) — all information that was simply unavailable to Kristen (see, e.g., Lave, 1982).

In short, in this case, Kristen was not familiar with the data or the data sources, and thus had no reason to form any hypotheses to care about testing. Kristen in fact implies (fairly directly) in the above exchange that if she had been able to form expectations (so that they could be contradicted, for example), she might have cared much more about the analysis and been much more invested in the results. To me, this illustrates that the ability to form expectations of the data may be a contributing factor in whether or not learners are able to engage with data analysis with the same sort of investment that we might observe among disciplinary professionals, who are likely to be
familiar enough with their data, its sources, and their discipline to form expectations and hypotheses to test using statistical practices.  

Additional examples. Each of the other participants (except Greg) had similar experiences that support this theme: Brian had little to no interest in the data analyses he performed until he performed a correlation between his computer usage and his steps, and the results contradicted expectations based on his personal experience. Britney formed and shared hypotheses about what her data would show before she even started collecting data. Sarah declared that analyzing her step data was far more interesting to her than she expected it to be, because it was far more variable than she expected based on her recollections of her daily activities. In each of these examples, learners were able to form expectations of the data because of their familiarity with their lives, and this helped them to form hypotheses and engage in analyses that could confirm or contradict their expectations. This helped learners to be more invested in the results of their analyses, and particularly to see data analysis as an instrument of inquiry (for use in testing assumptions about the world).

2 It should be noted that the student misunderstood this exercise, and had they understood it, they might have had a basis to form expectations of the data. The exercise did include the kind of meat in the hotdog.
Theme 2: Learners were more engaged when there was variability in the data.

Based on my analysis of the interviews and data exploration meetings, one of the contributors to whether or not data analysis using self-data engaged learners was whether or not the data was variable. Data that was more variable — particularly if that variation could be potentially explained by behavioral covariates (more on that later) — was more likely to engage learners in meaningful data analysis. This was first noticed in the experiences of a couple learners who expected the data analyses to engage to them, but were disappointed because there was little variability in the data. Absent that variability, they simple could not as easily bring themselves to care about the questions they asked about the data, or what the data revealed about their lives.

This indicates that self-data that is not prone to variation may not be a good way to invite learners into data analysis activities that matter to them. It is important to note that variability in the data is not a sufficient condition for data analysis to be seen as interesting by learners; it is possible for learners to see highly variable data as uninteresting. Elements of this theme could be observed in the experiences of all 7 of the participants in the study — each of them made comments that hinted that their interest in the data analysis was in some way contingent on or made possible in part by the variability in the data. I will share two illustrative examples below.

Example #1. At the beginning of his participation in the study (during the initial interview), for example, Greg specifically asked to track his heart rate, in part because he was studying to become a physical therapist, and felt that tracking his heart rate would lend insight into aspects of his life that are connected with those interests. He also chose
to track his sleep habits, but this was at least partly out of convenience (he was planning to wear the Fitbit activity tracker daily anyways, so it made since for him to collect that data). However, at the conclusion of the study, he revealed that exploring his heart rate was not nearly as interesting to him as he expected it to be. Conversely, he discovered that tracking his sleep was more interesting to him than he expected it to be. Consider the following exchange, in which I invited him to articulate the reasons why:

Jeff: So why was heart rate not as interesting to you as you thought?

Greg: I guess because I didn't see that it fluctuated, so there wasn't really anything, to me, that correlated as much with it, and so I was taking more steps, but my heart rate still stayed the same, or things like that. So it just didn't strike me as interesting enough to follow it I guess.

Jeff: Ok. And why was sleep interesting to you? Like why did that end up becoming...

Greg: I don't know, I guess it's just interesting to see different sleep patterns.

(Final interview, August 21, 2015, 00:06:48)

In this quote, Greg indicated (in line 284 of the passage above) that the lack of fluctuation — or variation — in his heart rate made it less interesting to him, in part because it meant that little that he did (such as physical activity) made a difference in the results. Conversely, his sleep data had tremendous amounts of variability, which he indicates (in line 289 of the passage above) that he considered to be more engaging as a result. Later in the same interview, Greg insisted that this lack of variation in his heart rate data was the only reason for his lack of interest in the analysis. He said, “With the heart rate, there wasn't much fluctuation with it, so that’s the only reason it really wasn't as interesting.”
Example #2. The same theme was observed Chris’s experience with self-data. As described before, Chris tracked his sleep, and based on his personal experiences, he actively formed expectations of the data and tested those hypotheses using statistical analysis — practices similar to those conducted by disciplinary professionals who are also familiar with their data. This demonstrates that the use of self-data placed Chris in a context in which statistics was being used as an instrument of inquiry. However, despite this, Chris did not learn anything meaningful from his analysis, and as he described below (in lines 293-294), he wishes that he could have asked a different question instead. During the final interview, I asked Chris about his sleep tracking. Consider the following exchange:

Jeff: After tracking your sleep, was it as interesting to you as you expected it to be?

Chris: Not so much. Mostly because it was pretty stable, I guess. I think just from what we did… it was pretty stable, pretty even across the board with not a lot of variation. So it wasn't quite as interesting to draw conclusions from. (Final interview, June 24, 2015, 00:12:13)

That is to say, Chris was not able to find meaningful insight from the analysis — again, because there was little variability his sleep duration data to account for in the first place. Here, Chris directly and explicitly attributed this to the fact that the data was “stable” without “a lot of variation.” This is not to say that the use of this data did not invite Chris into data analysis in precisely many of the ways we hope; it simply means that there may be further attributes of the data that could make the analyses more interesting. I asked Chris what would have made the data analyses more interesting to
him. He replied that tracking his bedtime and wake time (as opposed to sleep duration) would have been more interesting:

Chris: Yeah, I guess, more like with the sleep one, because that was the one, since we did sleep duration the first time, and there wasn't much variation, maybe like changing it into when you go to sleep or when you wake up. And overall it was fun, it was good to learn.

Jeff: Why would that be more interesting to you?

Chris: Since the sleep amount doesn't vary much, I feel like there would be a lot more variance in when it went to sleep, when it woke up. (Final interview, June 24, 2015, 00:53:50)

What is significant here is that Chris believed that tracking his bedtime and wake time would have yielded more interesting analyses because the measured values would be more variable; he stated once again that his disinterest in sleep duration was due to a lack of variation. We can see here evidence that variability in the data is an important contributor to whether or not data analyses are seen as engaging by learners.

Chris’s experiences (illustrated in this example, and coupled with Example #1 shared under the first theme) hint at some theoretical distinctions that may be important when moving forward in future research: mattering (the capacity to care about the results of analysis) may have some important distinctions from engagement (sustained attention) or interest (a more passive curiosity). Reflection hints at the possibility that disciplinary professionals may care about what they are researching, and engage in statistical analyses as instruments of inquiry — which are both precisely what we hope for learners — and also be bored with their data. This is apparently the case in Chris’s experience, and it seems related to the variability of the data.
The stated goals of this study are to explore whether (and under what conditions) the use of self-data may invite learners to care about what they are researching, and therefore undertake statistical analyses with different ends and goals than merely to please the teacher or pass a course; this is argued to be important because many statistical practices are learned as classroom exercises, and this may interfere with learners’ ability to think like a researcher or statistician. It seems that self-data helped Chris do precisely this (as illustrated in Example #1 of Theme 1); but this alone did not make the analyses revealing or interesting to Chris (as illustrated in this example). Variability in the data seems to be important on that front.

**Theme 3: Learners cared more about their analyses when the data took on a moral valence to the learners.**

Another theme that I observed in the experiences of the learners was that whether or not data analysis mattered to learners depended on whether the ups and downs of the data disclose themselves to learners as more or less preferable in some way. This was observed in the data — in cases where data analyses mattered to them, learners used terms to describe the data that indicated a preference for some data values or states over others. I use the term “moral valence” to describe this, by which I mean that there is an “good or bad” implicit in the “ups and downs” of the data, not necessarily in terms of any sort of abstract morality, but in terms of what is understood by the learners to be more or less preferred states of the world. What it means is that what is the case in the data is compared with what ought to be the case (in the minds of the learners).
For example, Kristen believed that spending many hours browsing the Internet on the computer was a failing of hers; she believed that she ought to spend less time. Similarly, she felt that her heart rate ought to be lower than it was, and this “ought” is substantially different from the prior “ought,” as it does not typically carry the burden of conscience that one’s browsing habits might. But both are, in the nomenclature used here, examples of data with “moral valence,” where the ups and downs can differ in greater or lesser degrees from what learners prefer to be the case. The conceptual opposite of this term might be data that learners treat with ambivalence (in the sense that learners simply do not care whether data values are high or low or anywhere in between). Evidence for the inclusion of this theme was found less often in explicit statements by learners, and more often in the way learners described the data while responding to other questions or inquiries. In short, learners did not as often provide this dimension as a reason for interest (or lack of interest) in the data; rather, it was the way they talked about the data that revealed this dimension while I was coding the data.

This ability to superimpose preferences on the ups and downs of the data differs from each of the other themes listed here. For example, data can be extremely variable, but learners might not superimpose a preference on the data. To construct an example, a person’s height demonstrably varies throughout the day; a person is, on average, slightly shorter in evening than they are in the morning (after a night’s sleep, see Eklund & Corvette, 1984). This predictable variability in the data, however, might not map onto any preferences of the learner. While trivially interesting to some, I imagine that most learners would be wholly ambivalent towards these daily, measurable variations.
Conversely, the ability to hold preferences about the ups and downs of data does not itself imply that a dataset matters to learners to the learners. Chris, for example, decided to track his sleep precisely because he has preferences regarding how much sleep he gets each night. It was these preferences, in fact, that informed his bedtime and wake time each day, which resulted in a data set that was not variable, and less interesting to him because of it. If Chris’s sleep duration had been more variable, those ups and downs would have been seen by Chris as more or less preferable; but this was not enough to make the data analyses matter. This theme was observed in the experiences of all 7 participants in this study.

**Moral valence can be provided by external benchmarks.** What is interesting here is that in some instances, learners used valenced language to talk about the data at least partly because of external benchmarks set by others. As described earlier, these external benchmarks can help learners form expectations of their data, and can in this way help them form hypotheses to test and to care about the results. In addition, those same external benchmarks can help learners imbue the ups and downs of the data with moral preference. Here are examples from two of the participants that illustrate this:

340 Sarah: Everyone says that you should take 10,000 steps a day, and I tried to reach that. (Final interview, September 2, 2015, 00:32:30)

342 Kristen: There's a lot of fitness goals that are like, "I need to keep my heart rate above so and so at least three times a week for 20 minutes," or whatever. (Initial interview, May 7, 2015, 00:27:50)

In Sarah’s case, she began to interpret days with fewer than 10,000 steps as less preferable, and days with over 10,000 steps as a success. In Kristen’s case, she expected to try and observe whether her heart rate matched external benchmarks for regular
exercise, and this would give her reason to see momentary rises in her heart rate as preferable, particular if they were associated with physical activity. In both cases, these external benchmarks — and the valence that Sarah and Kristen consequently attributed to the values of their data — are what contributed to helping these data sets matter to the learners. Consider also the following exchange with Britney, which took place during the first data exploration meeting. Britney chose to track her sleep, and during the first data exploration meeting, I asked Britney what she expects her mean daily sleep duration would be. She guessed that it was just above 7 hours. We used R to calculate the mean, and it was 7.7 hours. Britney responded:

345  Britney: Aren’t adults supposed to get eight hours of sleep each night?
346  Jeff: I think it’s a bit different for everyone. I thrive between 8 and 9.
347  Britney: Yeah, I have to get sleep. I have to be really careful, or else I’ll get grouchy. (First data exploration meeting, June 5, 2015, 00:34:10)

Notice here that Britney referenced an external benchmark against which she evaluated her own particular mean — she was implicitly asking, “Is my mean above, or below, the expected value?” This external benchmark is what allowed Britney to determine if the calculated mean was good or bad. Note her word choice (in line 320): “Aren’t adults supposed to get…” This implies that she sees some values (8 hours or more) as carrying the force of “ought” — people ought to get that much.

In contrast, none of the participants had any intuitive sense that their breathing or their blood pressure was problematic, or even what the data might look like on a chart. In short, without commonly known benchmarks for that data, they were unable to form expectations of what the data would show. But perhaps even more importantly, they were
unable to make value judgments about the data, or the results of their analysis. Brian’s experiences with the data illustrate this rather well. Brian chose to track his sleep, his steps, and his computer usage. Of the participants, Brian seemed to care the least about the data analyses we performed, or the results of those analyses. He repeatedly remarked, during and after the study, that while he enjoyed participating, he did not find the data analyses very engaging, nor did he care about what he was tracking.

However, Brian was nonetheless insistent that other options, such as tracking his heart rate or his weight. For example, consider Brian’s response when I asked him, during the final interview, if tracking and analyzing his sleep, steps, and computer usage were as interesting to him as he expected:

> I think [they are] still more interesting than heart rate and weight and everything, just because with heart rate I don't have much of a frame of reference of what it should be, you know what I mean? [Sleep, steps, and computer usage] are the ones that I like … because they're things I actually feel like I care about or I think about, you know what I mean? (Brian, final interview, August 21, 2015, 00:11:23)

Brian’s comment, “They're things I actually feel like I care about or I think about,” may involve a number of factors, but Brian implies here that his ability to care or think about them is at least in part because he has a “frame of reference” for what they should be. This is what gives him the ability to treat the ups and downs of the data as more or less preferable—and not just in relative terms, but also in absolute terms.

In some instances, however, the data is valenced by internal benchmarks set by the participants themselves. There are no publicized benchmarks for “acceptable” computer usage, but Kristen had an intuitive sense that she was using her computer too much (even if her intuitions did not supply her with specific benchmark values). In this
case, it seems that the benchmark is found in the data itself, in the comparison between low-usage days and high-usage days: the low-usage days became the benchmark. For example, during the first data exploration meeting, we looked at the daily means of Kristen’s computer usage, and displayed them on a bar chart. As Kristen observed the ups and downs of the chart, she exclaimed, “This is ridiculous … the over 400 minutes one. And this one too [a bar with a similar value]. I don’t know what I was doing” (First data exploration meeting, June 5, 2015, 00:22:30). First, note that Kristen imbues valence on the data by calling the highest value “ridiculous” (a term implying a sort of disgust with herself for using the computer that much). Second, note that this became a benchmark by which she could compare and evaluate other values.

**Additional Example:** The importance of “moral valence” — again, referring to when data discloses itself to learners as more or less preferable — can also be observed in Brian’s other self-tracking activities. During the second data exploration meeting, Brian explored whether he took more steps on weekends than on weekdays. Consider the following exchange that took place during the final interview, in which I followed up with Brian about analysis we performed to answer this question:

355 Jeff: We also asked whether you take more steps on weekends than on weekdays. How important was the answer to that, or that question to you?

356 Brian: When you say important, what do you mean?

357 Jeff: I guess... How much does it matter to you that the answer was one way or another? Or how much did it matter to you that we found an answer to the question?

358 Brian: I don't think it was that important to me, again it was just more interesting. I don't really have a preference of how many steps I take either way, so it wasn't important in that sense where I was trying to confirm something. (Final interview, August 21, 2015, 00:24:14)
Here, Brian distinguishes between “interesting” and “mattering,” an interesting distinction (no pun intended), which may or may not lend support to the distinction made earlier between mattering and engagement (in which learners can care deeply about their analyses, but still be bored by the process). However, it is less important to the subject of this section. The last sentence of this exchange was revealing: *he did not see the ups and downs of his steps data as being more or less preferable.* The data had no *valence* to him. This was confirmed again moments later, in a follow-up question:

365 Jeff: Ok. So are there other questions we could've asked about your steps, do you think, that would've mattered to you more?

366 Brian: No. I mean I don't really care about them. It's not that important to me if I've taken this many steps. (Final interview, August 21, 2015, 00:25:19)

In these last two quotations, Brian highlights clearly the reason for the inclusion of this theme as one of the contributing conditions for mattering: Brian was deeply familiar with the life activities that he tracked, *and* the data had variability, but because the data did not take on a valence (where the ups and downs manifested themselves as more or less preferable in some manner), Brian simple did not *care* about the results of the analyses he conducted. The common thread here seems to be that if a learner cannot look at a measurement and say, “that’s good” or “that’s bad,” they are less likely to find the data collection and analysis meaningful. Sarah could say that about her step counts, and Kristen could say that about her heart rate measurements, in part because of externally supplied and publicly known benchmarks; in contrast, Brian could *not* say that about his heart rate measurements.
I would also venture to say that likely *none* of them would be able to say that about a breathing rate measure (without at least looking it up first). Except for those with known medical issues, most people are unaware of what a “good” breathing rate is (for evidence, my challenge to readers would be to guess — off the top of their head — the number of breaths per minute that is considered “normal” by physicians, and what values would be considered alarming or hyperventilating). While such benchmarks may indeed exist, they are not as well known to the lay public. My suspicion — which, admittedly, cannot be confirmed without more evidence, but is a hypothesis grounded in my analysis of the experiences of the learners in this study — is that if there were similar highly publicized standards for breathing rate, more of the participants in the study would have expressed interest in tracking their breathing using the Spire device. As it is, I suspect that no participants expressed interest in doing so at least in partly because they had no prior way to attribute such valence to the data; there were no *commonly known* benchmarks against which they could measure their breathing, or wonder whether they were meeting.

(As an aside, it would be deeply interesting to see if more learners expressed interest in tracking their breathing if I had introduced the option in this manner: “Another options is to track your breathing rate. The normal breathing rate for an adult at rest is 12 to 20 breaths per minute. A breathing rate under 12 or over 25 breaths per minute while resting is considered abnormal. This device could allow you to measure this rate on a minute by minute basis.” Such an approach would have introduced *valence* to the potential data from the outset — giving its highs and lows meaning such as “normal” or
“abnormal” — and potentially have invited learners to care more about tracking and analyzing their breathing data.)

**Theme 4. Learners cared more when they tracked data and asked questions that related to ongoing concerns.**

An additional theme observed across many of the learners’ experiences with the self-data was that the questions they asked and the analyses they performed with the data seemed to matter most when they related to an ongoing concern of the learner. This concern could be a bad habit that they wished to correct, an injury that they were trying to overcome, or anything that made the actual values of the measurements taken less preferable to the learners (and thereby gave them reason to seek to understand, account for, and seek to change those values). This dimension could be summarized by saying that self-data collection and analyses mattered more to learners when they wanted to change something about their lives.

This is distinct from the theme of “moral valence” because a person can *not* have a problem that they are trying to address, but still find the data engaging because of a strong sense of valence that they assign to even *preferable* values. This was observed, for example, in Greg’s experiences — as mentioned above, he expressed specific interest in his sleep patterns, and he asserted that analyzing his sleep patterns was engaging specifically because he felt that a good night’s rest was important (in short, he imbued moral valence into the ups and downs of the data). However, he did *not* believe that he had bad sleep habits, or that he needed to correct his sleep patterns at all. In short, the
data analyses related to his sleep habits did not plug into an ongoing concern or problem, and yet Greg found them to be engaging and interesting.

However, the converse seems unlikely to be true; feeling like one has a problem to address inherently imbues the data with valence, and makes some values more preferable to learners than others. One could say, then, that while external benchmarks provide learners with context for imbuing data with moral valence, so can the ongoing personal concerns of the learner. Professionals and academics who engage in statistical inquiry have usually found reasons to care, such disciplinary interests, passions, or investments that motivate their data collection and analysis. But even undergraduate students who are advanced in their majors have often yet to develop these sorts of passions, interests, and disciplinary investments, or perhaps have had little exposure to data analysis that is motivated by such passions. The use of self-data offers the possibility of connecting the data analysis to the personal concerns of the learners, and to the extent that this happened, participants in the study seemed to care more about the analyses they conducted. This theme was observed in the experiences of all 7 participants.

**Example #1.** Britney’s interviews and experiences provide evidence for this theme. In my conversation with Britney during her initial interview, I asked her about things she had tracked about herself in the past (which, she responded, included her steps, car mileage, her calories, and finances). When I asked why she tracked these things, she replied:

> So the only reason I would pay attention to that, is if I was planning on making a change. Or if I was in the middle of making a change. So when I started tracking my steps, it was because I just had knee surgery, and it was really important to get that 10,000 in. (Britney, initial interview, May 13, 2015, 00:17:28)
In other words, Britney started tracking her steps (prior to this study) because there was an immediate problem — a recovering knee — that needed her attention.

Britney indicated in the above excerpt that the same is true of other aspects of her life that she has tracked. Britney’s additional comments are particularly revealing. She continued, “But I wouldn't track without knowing that I was changing, or track the change I was trying to make.” As I asked for clarification, the following exchange occurred:

Jeff: Ok, so you say that you only care about it when you're making a change. Is that what you said?

Brittney: Yep.

Jeff: So, in what context...

Brittney: What makes me care?

Jeff: Yeah.

Brittney: If I have a problem.

Jeff: If you have a problem?

Brittney: Yep.

Jeff: And what constitutes a problem?

Brittney: Ok, so walking was my knee surgery. So I had a problem, or I needed to solve something, I needed to strengthen my quads and my legs and it was suggested that I get my 10,000 steps in. So I did that. When I’m tracking my nutrients, it's usually because I'm feeling crummy and I know I'm eating a lot of fast food. So I’m like "Well..."

Jeff: That happens to me sometimes.

Brittney: Yes. And I’m like ugh. So I’m like "Well, I’ll track my nutrients, and make sure I’m getting enough vegetables and enough fruit and enough protein in a day. (Initial interview, May 13, 2015, 00:17:59)

I do not feel the need to explicitly unpack the entirety of this exchange, except to say that Britney explicitly states that having a problem or an ongoing concern is an
essential criterion for whether or not she cares about data that she collects. What is interesting about this is that Britney is the only participant that expressed any interest in tracking her stair flights. In her final interview, she said that if she were to choose again, she would add stair flights to her list of things to track. She explained, “I'm trying to get back into running stairs, and I do Old Main sometimes,” in part because of her ongoing knee problems. So it is revealing that the only learner with a knee problem is also the only learner who considered tracking her stair flights.

**Example #2.** Previously, we saw that Brian had quite a bit to say about his disinterest in tracking various aspects of his life. In contrast with Britney and others, he had applied very weak valence to the ups and downs of his data. However, he consistently carved out space for a potential exception: if he had a problem with some aspect of his life, he believed that he would be interested in tracking and analyzing it. Consider, for example, the following statement (which took place during the final interview): “Again with weight and breathing and stuff, I’m not like a super health nut or anything so I just don't care that much as long as I feel good.” The subtext here, however, was that if Brian did not feel good, this kind of data would then start to carry significance to him.

Another example can be found in Brian’s reaction to analyses related to his computer usage (which he described as uninteresting to him). During the final interview, I asked Brian if he would ever consider analyzing his computer usage again in the future: Brian: No, I don't really beat myself up if I use it too much. It's not something.... I just kind of do it whenever, so.
Jeff: What about the phone? What if you were able to do it on your phone?

Brian: Phone? Probably I might, because personally I feel like a phone is more of a waste of a time because you can do less on it. I think I would be more interested in tracking phone than computer, because my phone is something that I'm trying to use less, but my computer isn't. (Final interview, June 20, 2015, 00:16:31)

Here, Brian stated that he might consider analyzing his phone usage in the future, because it is something that he is trying to use less — he felt that his current phone usage habits were problematic and needed to be changed. This is one of the few examples in which Brian indicated that self-data analysis might matter to him in any way. In every other aspect of his life that was available for tracking, he felt he had nothing that needed changing, no problem that needed addressing, and therefore little interest in the results of the analysis. The take-away from this example is that self-data does not automatically plug into the concerns of learners, merely because it is about the self; learners care more if there are ongoing problems or concerns that they are trying to address, and which the data can help them address.

**Instructor-guided questions can help plug self-data into ongoing concerns of learners.** It may be tempting to believe that if self-data relates to and can potentially provide insight about some ongoing concern, interest, or problem of the learner, that the learner will automatically initiate and generate fruitful questions to ask about the data. This is not necessarily the case, as I observed in this study. For example, Kristen implicitly saw the study as an opportunity to overcome her habit of becoming absorbed in mindless, online entertainment, by tracking her computer usage using RescueTime. She was worried that she wastes too much time on the Internet, for example, and thinks that tracking her computer usage will force her to pay more attention to productivity habits.
She explained that she was attracted to the study in part because she has “always wanted to pay more attention to stuff that [she] does.” Her desire to use her time more wisely was rooted in the kind of person she wanted to be:

So many times in my life I'll just get on the Internet and it keeps going and keeps going, and it doesn't make me happy. … It's so bad. It's so unhealthy and everybody does it. I feel like if people could just pay more attention, and be more conscious, more in-the-moment thinking about what they really want from life in general, and not be distracted by this instant entertainment, then they might like — as a human race, we could be so much better and more productive. (Kristen, initial interview, May 7, 2015, 00:24:49)

Kristen’s concerns here were, in essence, concerns of conscience; she discussed the kind of experience she wants to have on her deathbed — she did not want, in that moment, to be able to reflect on nothing more than the online media she had consumed the previous week. Later in the interview, Kristen explained further that she would love to start a hobby, but that instead, “I go on the Internet I read a lot of articles and stuff. Actually Facebook is my gateway time-waster, because everybody posts articles or videos that I do love” (Initial interview, May 7, 2015, 00:44:55). In this way, distractions like Facebook and Kristen’s habits of computer usage were keeping Kristen from things she considered to be more important (like hobbies, productive engagement with friends and family, etc.). She wanted those habits to change.

During the study, I took great care to try not to “manufacture” mattering during the data exploration meetings. To design research questions that specifically plugged into concerns that she had, but which she herself did not ask or initiate, seemed as though it might do that (that is, manufacture the very sort of mattering that I am investigating). While I invited Kristen to initiate and ask questions of her own, the questions I prepared
in advance (in case she did not ask any of her own) were neutral to her ongoing concerns. These are the questions that Kristen defaulted to. This is not to say that none of the questions that Kristen asked about her data were related to her wasteful time habits. For example, two of the questions I prepared in advance (“Do you use the computer differently on weekends than on weekdays?” and “Do you use the computer differently on rainy days than sunny days?”) did relate to these ongoing concerns about her habits. This was not intentional, since I prepared similar questions about her sleep habits and her physical activities.

These questions, however, did not yield any in-the-moment insights for Kristen; she had little reaction to the results (there were no statistically significant differences) during the data exploration meeting itself. During the final interview, Kristen mentioned that she felt that she wishes there had been a difference between her weekend and weekday computer use. She explained,

> I kind of wish it had said that I used it more on weekdays than on weekends. Because on the weekends, I feel like I'm doing other fun things, and would not have time to get on the computer. I guess if that was the answer, it means that — or it could mean that — I'm not having as many adventures as I think. (Kristen, final interview, June 24, 2015, 00:40:23)

Here, we see that the analysis of the data did seem to “plug into” her concerns about her wasteful time habits, which helped Kristen to be invested in the data more than she might with contrived data (can we imagine a student, for example, saying about the results of an statistics assignment with contrived data or data provided by an instructor, “I wish it had shown that…”?). However, the analysis did not seem to yield anything interesting that would help her *address* those habits.
The only other question that Kristen asked about her computer usage was initiated by her (without prompting from me): “Does how long I sleep depend on how much I use the computer?” (We performed a correlation, and found that there was no discernible connection between her computer usage and her sleep patterns.) Kristen chose this question in part because we were going to use correlation to explore her data, which required her to ask a question about the association between two variables she tracked in her study. When I asked Kristen why she chose this question, she did connect it to her broader concerns about her wasteful time habits. She explains:

409 Because I don't know if there's necessarily a causation there, but I feel like the
410 nights when I stay up doing homework or something, I also have less self-control
411 and I have less focus. I'm really tired, and I don't want to think about this for three
412 minutes, so I'm going to go look at Facebook or something like that. (Kristen,
413 third data exploration meeting, June 19, 2015, 00:15:47)

In short, Kristen suspects that she spends more wasteful time on the Internet or her phone when she is tired, and so she is curious if late night, extended homework sessions lead to less sleep. So she seems to justify this question at least partly in terms of how it might help her understand potential contributors to her wasteful time habits; however, if I had not asked her specifically to think of a question that required correlation to answer, and which used variables she had already tracked, it is not clear to me at all that she would have asked this particular question. I wonder if this might have been different had we made that a central question in her analysis — that is, if Kristen had tracked data, asked questions, and performed analyses explicitly to help her understand and perhaps change her lifestyle. For example, if we had made understanding Kristen’s time usage — with the intention of improving her lifestyle — a central priority, we might
have started tracking her phone usage the moment she started to see a shift in her daily habits. In addition, we might have been less interested in tracking (or continuing to track) her steps and heart rate, which were at best tangential to those concerns.

In short, Kristen did have ongoing interests and concerns, and using statistical analysis to explore her computer usage data showed promise in connecting to those concerns; but it is important to design the learning experiences in such a way that those ongoing interests and concerns are made a focal point of the analyses. The use of self-data can plug into ongoing life projects and concerns of learners, but it does not necessarily happen on its own. Just because a learner is tracking information that could yield insights into ongoing concerns does not mean that they’ll ask questions that do yield such insights (even if such questions could be asked). Perhaps “mattering” can, in this sense at least, be “manufactured,” where the instructor scaffolds the development of questions about the data so that they tap into existing concerns and life projects.

**Theme 5: Learners cared more when they could investigate potential covariates.**

A corollary to the second theme above ("Learners were more engaged when there was variability in the data") was that self-data seemed to matter not just when there was variability in the data, but when there were other covariates (or at least potential covariates) that could be tracked and analyzed as well. In other words, learners cared more about the results of their data analyses when they were not looking at aspects of their life in isolation, but in conjunction with other tracked variables (or other aspects of their lived experience) in efforts to explain variation observed in their data. Learners seemed less likely to care about self-data if what they tracked was not expected to have a
measurable influence on some other aspect of their life, or was not expected to be influenced by their lifestyles or activities.

For example, tracking sleep was seen as engaging to a few of the participants in the study; but tracking sleep and mood, and exploring the effects of one on the other, was much more engaging (or at least potentially so). Learners seemed less likely to care about self-data if what they tracked was not expected to have a measurable influence on some other aspect of their life, or was not expected to be influenced by their lifestyles or activities. A corollary of this dimension, which I nearly treated as a separate theme, was that self-data seemed to matter only if learners felt that they had some measure of control over what they were tracking. In any case, learners wanted to know more than just a descriptive account of their activities (e.g., which days they slept most), and wanted insights into possible reasons why the data looks as it does, and possible insights into how to enact change in their lives — something that they felt was made more possible by tracking multiple aspects of their life. Evidence for this theme was found in the experiences of all 7 participants.

**Example #1:** As we have noted before, Brian had an almost passionate disinterest in the data that he collected about himself; however, he was very nonetheless vocal about what was most interesting when performing analyses with his data, and what would have made the analyses more interesting. During the final interview conversation, I asked Brian what he might track, and what kinds of analyses he might want to perform, if he could participate in the study over again:
Brian: It might have been interesting to do mood and sleep, or mood and steps. … People say things like, when you exercise more you have a better mood, so it would be interesting to see if it's true.

Jeff: Ok.

Brian: I think the correlation was the most interesting, to be honest. I think that's more interesting, in theory, than just "When do I use computers more?" And stuff like that. Just to see how things affect each other rather than just, "This is what I do." You know what I mean? For example, when we were doing the computer usage by day of the week, kind of the question we're asking is, "What is your behavior?" But then when we were doing correlation, it was "How does your behavior affect other behavior?" I think that's more interesting to me individually than just saying "This is what is."

Jeff: So as far as the kind of questions you want to ask, you want to ask about correlation?

Brian: Yeah, I think correlation is more interesting to me, especially with personal data. It's hard to have a frame of reference when you just look at data. It's like, "You took this many steps," but I don't know if that's a lot or a little, so it's more interesting to me to see how my steps affect other things, than just the mean of my steps on Tuesdays. (Brian, final interview, August 21, 2015, 00:13:54)

Brian’s comments here lend support to the possibility that, in addition to variability in the data, learners are more likely to be engaged in the data if there is an expectation that such variability can be explained by, or explains, the variability in some other aspect of their life. He specifically stated that descriptive questions (e.g., “How much do I walk?” or “What does my heart rate look like?”) were less engaging to him than questions that attempt to connect tracked variables with potential covariates. I think that this may be true generally.

Example #2. During the initial interview, Peter indicated that he wanted to track his sleep because he felt that he had a problem sleeping. However, he also wanted to track his computer usage, because he was curious if his sleep and his computer usage
were covariates, and whether or not he could influence his sleep patterns by adjusting his computer usage. He stated:

> [I]t would be interesting for me to actually take some time to track my sleep, to see what my patterns are, and to see what affects when I go to bed, when I woke up. Maybe that could influence what my behavior is. That was actually really interesting to me. (Peter, initial interview, May 14, 2015, 00:27:14)

As we conducted correlations during the third data exploration meeting, we did not discover any statistically significant associations between his computer usage and his sleep. Peter was disappointed. In addition, during the study, he did not wear his Fitbit during the daytime; he only wore it at night, to track his sleep. This meant that Peter was the only candidate in the study who did not obtain step data. After finding no statistically significant correlation between his computer usage and his sleep, Peter became frustrated that he had not tracked his steps as well. During the final interview, he explained:

> And when we learned about [correlation] in class, I was like "Oh! I hope we do this, you know, with Jeff." And when we did, I was like "Oh it's time, we're going to get some data that could be correlated, we're going to do some regression." And then it's "No." And I was like "Aaagh! Yeah it is!" That's why I was like, "I really wish that we could get more data," and I really wish that we could've gone longer, maybe got some more data to see. (Peter, final interview, June 24, 2015, 00:28:38)

Here, we see evidence that Peter is actively interested in and caring about his sleep data; in addition, he saw correlation as more than just a classroom exercise, but also as an instrument of inquiry that could be used to illuminate something about his own life — something that he expected, and in fact hoped, to use outside of a classroom context. During the final interview, I asked Peter what he would track if he could do the study over again. He replied that he would track his exercise levels, his sleep habits, as well as his phone usage (in addition to his computer usage). Note the following conversation:
Peter: Cuz what I wanted to be looking at as well was my exercise level, and I guess I could put that in a general exercise category that might include steps and heart right. So that, combined with sleeping, and how much I use electronics would be really interesting.

Jeff: Awesome. What would be interesting about those? …

Peter: … I feel like it would be cooler to see the correlations, and you might be able to see a closer correlation, and have a better understanding of how certain categories are related, and how it may effect one another. … Cuz I kind of not regret not wearing it around every day, even though we were just focusing on sleep, I felt like it would be cooler to like also look at the steps to see how that might've played into it too. …

Jeff: Ok. So, when you said you wish you had worn it more, why is that?

Peter: I just feel like it would've given us more data, and I feel like with more data you would get more, you'd be able to make more inferences, see more correlations. (Peter, final interview, June 24, 2015, 00:09:49)

Here, Peter confided that he really wished he had worn the Fitbit during the day; he felt that the data analyses would have been more meaningful to him, if he had been able correlate his sleep with other activities in his life (beyond his computer usage), in order to see what else might account for variation in his sleep patterns. For example, after analyzing his sleep habits, he wanted to know what kinds of activities — such as computer and phone usage, or his daily steps — might influence his sleep duration and quality. In addition, he explained, “What I cared about most was why. Why I couldn't sleep, and what could be related to that. So I looked at the aspects in my life that were…the only aspects I knew that were related, that could be related” (Peter, final interview, June 24, 2015, 00:27:33). In each of these quotes from Peter’s interviews, he explicitly stated that his interest in questions related to his sleep depended on his ability to associate his sleep habits with potential covariates, so that he could make inferences about the potential consequences of his behavior on his ability to sleep.
If statistics instructors and researchers wish to help learners step into a learning context in which they can engage with statistical inquiry with an investment in the research questions comparable to those asked by disciplinary professionals — in which the analyses matter as more than mere classroom exercises, but as means of interrogating the world in a way that advances ongoing interests and addresses ongoing concerns — then using self-data may advance that goal. The truth is that research, whether contrived in a classroom or conducted in the field — often takes place at a distance from the lived experiences of the researchers, and has very little impact on their personal choices and activities. As described earlier, disciplinary professionals have usually developed an investment in their discipline or science that motivates their research — and investment that most undergraduate learners simply have not developed. The use of self-data, however, can potentially plug statistical inquiry into the ongoing concerns and life projects of the learner, thus inviting them to care about the data they are analyzing and the results of their analysis.

What I have outlined above are five themes, based on the experiences of participants in this study, that help identify contexts and conditions in which self-data may be more effective at facilitating just this sort of investment in the research process. These five (broad) themes are not intended to be exclusive or exhaustive; there were other themes observed, but not included here, because they were observed in the experiences of only one or two of the participants. In addition, there are further insights
that could not be distilled to a single statement or theme, and can only be discussed in the context of the broader narratives of the learner. Some of these insights involve the nature of the learners’ concernful involvement with the data. In what follows, I will explore two of these unique cases and narratives, and highlight the insights this case may offer in how self-data might be productively used to help statistics matter more to learners. Then, I will highlight some of the narratives of other participants.

**Sarah’s Narrative Arc**

This first narrative tells the story of Sarah, a participant whose experiences with the data exploration meetings we detailed earlier (in Chapter 5). Her narrative illustrates a perhaps paradigmatic example of the successes of using self-data in a statistics learning setting — as she analyzed data about herself, she understood the uses of statistics as a tool for inquiry in a way that she did not before, and developed an investment in her analyses that she did not have before. As explained in the analysis section, dramaturgical coding helped me to make informed inferences about Sarah's personal narrative, rich with details about her objectives, values, emotions, etc., as well as the role the statistics course plays in her narrative; similarly, dramaturgical coding helped me to uncover the role that participating in this study, as well as using self-data to practice statistical concepts, played in her personal narrative. In this section, I will articulate different elements of Sarah’s story (the values and objectives of the protagonist, the obstacles in her way, and the climactic realization that reframed her path forward). Through all of this, I will assume that Sarah is the protagonist of her narrative. I will then discuss how each of these
elements help us to better understand the possibilities that the use of self-data offered for Sarah’s ongoing concerned involvement in her learning of statistics.

**Objectives.** Sarah is dedicated to completing a degree in mathematics teaching, with a minor in biology. This involves taking a number of math and statistics courses, and then completing the university’s secondary education program (a program designed for training teachers for working in a secondary education environment, within their subject of study). Her intention, she explains, is to teach math on a college level. To get there, she explains, she has to first “teach high school math.” She explains, “I’m going to teach high school for four years, because I’m getting scholarships that I have to teach four years to pay it back, and during that time I’m hoping to get my master’s in education, and teach college when I’m done” (Sarah, initial interview, May 18, 2015, 00:02:13). Her academic endeavors are oriented towards this long-term goal; one could say that teaching math on a college level serves as the principal *objective* of the Sarah’s long-term narrative (with getting a bachelor’s and then master’s degree, while teaching math on a high school level, being strategies for pursuing her objective).

Sarah was 21 years old at the time of the interview, and as a recently returned missionary for the Church of Jesus Christ of Latter-day Saints, she values the family ideals promoted by her religious community. “I would like to be a stay-at-home mom,” she explains — a projection of the future that is likely informed by longstanding traditions within her faith community, which treats motherhood as the “highest calling” that a woman of faith can pursue, and which has discouraged “employment outside the home unless there is no other way that the family’s basic needs can be provided” (Oaks,
These faith values are reflected in Sarah’s description of her possible futures: “But I don't know if that's feasible. If my husband doesn't have a good enough job and we need the income, then I’d probably teach, or... I really like kids, so I could run a daycare maybe” (Sarah, initial interview, May 18, 2015, 00:05:58). A professional life of teaching is a sort of “back-up” plan in Sarah’s projections of the future — a back-up plan that she is treating as default until she marries and has children of her own, and in which her family is financially stable enough for her to stay at home and raise her children. What is important about this, though, is that her ambitions to be a math teacher reflect a provisional future (at least to some degree).

Sarah also highly values personal responsibility in academic contexts — she prefers participating in educational activities when learners are self-motivated, rather than compelled by policy to participate. This is reflected in her reasons for preferring college teaching over high school teaching; when I asked why she hopes to teach college instead of high school, she explained:

[H]igh school kids... I’ve worked with them, and they have a lot of discipline problems, and it's harder to get them to want to learn, whereas when you're in college, you're in that class and you're paying for it, and you go to class and learn if you want to, but if you don't then it's not the professors fault, you know? (Sarah, initial interview, May 18, 2015, 00:03:18)

This is also reflect in her attitudes as a learner; for example, she expressed a willingness to retake courses in order to obtain content mastery that she feels to be essential to her education, even if not required for her degree. Her willingness to voluntarily retake an advanced math course (a willingness not merely expressed in this interview, but enacted in her past behaviors) demonstrates her preference for self-
directed, comprehensive learning experiences — as a consequence of this preference for self-directed learning, she explains, “I'm a pretty self-motivated person, so I’m not too worried about not learning the stuff in this class” (e.g., she does not expect to fail the course or fail to learn the material in the course; Sarah, initial interview, May 18, 2015, 00:15:37).

Obstacles/Conflicts. At the commencement of this study, Sarah viewed statistics courses as one of the chief obstacles in pursuing her long-term objectives. When I asked how the statistics course she was currently taking factors into her degree, she replied that the course is required for her major, and is also the prerequisite to two other courses that she was planning to take in the upcoming fall. In addition, she explained that it is also the first statistics course she has taken since completing high school. At this point, I started to explore more fully how statistics plays a role in her projections of the future. Note the following exchange, in which I prompt her to explore how statistics might help her advance her long-term objectives and goals:

464 Jeff: How do you think taking this statistics course that you're taking right now will help you personally?
465 Sarah: I think it will be good, because I’ll need that information for the rest of my courses, and I guess that's it. I don't know if it would help me personally, because I don't... I don’t know.
469 Jeff: That's fine. If the answer is "it won’t...,” that’s perfectly fine. I guess I should have asked, do you think it will help you personally?
471 Sarah: Probably not. I don't gamble, and I don't really do a lot with statistics in my personal life, so I don't think it would help very much. (Sarah, initial interview, May 18, 2015, 00:09:34)

In the first part of her response, Sarah asserts that learning the material in this statistics course is vital for her participation in future university courses — and this belief
seems resilient, even in the face of her admission that statistics will not be personally useful to her, and in the face my counter-questioning. I asked her what would happen if she were to pass the course, but fail to learn the material, to which she replied that she would not be able to complete her other courses. She explains:

474 I know that it's essential to the rest of my grades, and I need to get good enough grades to keep my scholarships, so if I don't learn the stuff that I'm learning this semester, then it'll affect me for next semester, and I won't get as good of grades, so that's my motivation is to keep my grades up so I don't lose my scholarships because then I can't go to school. (Sarah, initial interview, May 18, 2015, 00:14:35)

In other words, Sarah views her statistics course as a true prerequisite; the statistics course is not merely an obstacle on paper (a concern only for administrators), it is an obstacle in fact — she needs to climb over that mountain, not merely travel around it. In fact, she says that if she were to pass the course, but then have her memory wiped, she would voluntarily take the course again to avoid troubles in future courses. She claims to have done this before in the past with Calculus — she retook the course because she could not remember what she had learned while taking it. She explains, “Math builds on itself so you can't really just skip a class and not expect any consequences.” In short, taking statistics is important to getting her degree, which is important for being able to teach math. There is a possibility of teaching statistics, which would make her learning directly applicable to her professional endeavors, but she sees this as only a possibility, and one she hopes to avoid. Consider the following exchange:

480 Sarah: … I’m not a big fan of statistics, but I like teaching the high school kids algebra and geometry and stuff.

482 Jeff: So you're not a big fan of statistics: why is that?
Sarah: I like math for the logical part of it, like doing equations and getting the right answer. And statistics is more of a practical use, which doesn't really make sense, but I don't really like doing practical math as much, like physics or anything like that.

Jeff: Ok.

Sarah: So that's why I like math better than the statistics part of it.

Jeff: Do you have any insights into why that might be, and why you don't like the practical side of math?

Sarah: I don't know. I haven't been able to figure it out yet. (Initial interview, May 18, 2015, 01:05:11)

This is where Sarah’s attitude towards statistics is revealed to be a little bit confusing and simultaneously deeply interesting: Sarah believes that statistics is a form of applied math, and as such, she sees it as separate and distinct from the kind of math that she wants to teach. Sarah also believes that she has had a talent for it, so to speak, since she has been in junior high, that she attributes in part to good math teachers. Her passion for math, however, seems to be confined primarily to what she sees as the abstract components of the field, rather than to the practical applications of mathematics in real-world settings.

However, while she believes strongly that understanding statistics is essential for completing her degree, the language she uses to talk about the statistics course indicate that she sees it obstacle to her goal. For example, consider the following comment from Sarah, which took place at the beginning of her final interview:

[Last semester I was really freaking out in the spring, because I knew I had to take a few more stats classes, because I'm a math-stats major. That had changed during that semester because I was going to do just math and then biology teaching, but Utah State doesn't have a biology teaching minor. So I have to do math and stats, so I was like, "Ok, I'll just push my way through and make sure that I do well enough that I don't have to re-take classes.” And then over the]
summer I took this class, and it wasn't what I was expecting. It was harder than I thought, and I got a C, but I passed and that's all that's important right now.

(Sarah, final interview, September 2, 2015, 00:07:28)

As discussed in the analysis section (where this passage is used to illustrate my analysis protocols), she indicates that a few months prior, she was “freaking out” about needing to take more statistics courses. This word choice, in context, seems to convey a state of fear or anxiety experienced when stepping into a future that involves taking more statistics courses. The statistics course itself is implied by this to have been treated as an obstacle in her story, a source of conflict in the way of her objectives. This is illustrated by her use of the words “push through” when talking about how she saw her statistics course — the statistics course disclosed itself as an obstacle in the way, almost like thickets and foliage across her path, impeding her progress. It was “harder than she thought,” implying again that it was an obstacle.

In summary, Sarah’s objective is to teach college math, and she hopes to avoid having to teach statistics; in addition, she is compelled to statistics courses because, according to her, the university combines math and statistics. Statistics is not seen as valuable to her in any other capacity. While she believes learning statistics is necessary for passing her future courses, it is something that she would avoid altogether were it not necessary. Her attitude towards statistics is quite negative; she thinks of it as fundamentally different from the mathematics that she loves and wants to teach. In all these ways, statistics is revealed to be an obstacle in her broader story; a challenge that she must overcome in order to pursue her objectives.
**Plot/story.** The overall arc of Sarah’s story (at least, the part of her story that involved her participation in this study) can be described as either an epiphany narrative or a conversion narrative. Her attitude towards statistics changed dramatically over the course of the story, with the focal point for her shift in perspective taking place over the course of the second data exploration meeting. Here, I will unfold this narrative as I describe the change in attitude that took place.

Prior to her epiphany moment, beyond helping her with future university courses, however, Sarah did not expect statistics courses to be useful to her personally. Her comments above reveal a conception of statistics that is somewhat narrow: Sarah seemed to believe that statistics was primarily about *probability*, and that statistics is therefore useful for the layman solely for gambling. In addition — as explained earlier — she saw statistics as an obstacle that she must overcome or “push through,” a nuisance that she must endure. And for most of her participation in the statistics course, she experienced her statistics learning in just this way. In her communications with me via email on July 8, 2016, she explained, “The stats course is kicking my butt. It's been really difficult for me. But I'm making it work.” And during our first data exploration meeting, she also expressed similar difficulties. Consider the following exchange:

502 Jeff: So, tell me how the course is going?  
503 Sara: It’s… good.  
504 Jeff: I sense a little bit of hesitation…  
505 Sara: It’s hard. I don’t like stats.  
506 Jeff: Why not?
Sara: I don’t know when to use the different stuff, I guess. I don’t know. (Sarah, first data exploration meeting, July 16, 2015, 00:00:15)

Again, statistics is depicted as difficult; she does not enjoy it; and it is confusing to her. True to her earlier comments about her skills at math, she is not having trouble applying appropriate algorithms and getting the right answers; rather, she is struggling to understand the contexts in which different algorithms are used, and what for. In other words, she is struggling because she does not know the application of what she is learning. Earlier in the study, she stated that she does not like statistics as much precisely because it is more application-based. Confused by the contradictions between this and her other statements, I asked for clarification during her final interview. She replied:

Because you use it in situations where it's not applicable to me. I'm never going to do a drug study, and I’m never going to do stuff like that because I’m going to be a teacher, so that wasn't really applicable. (Sarah, final interview, September 2, 2015, 00:05:55)

In other words, because she plans to be a math teacher, most of the applications offered by instructors in previous courses were entirely inapplicable to her, and this is why she found statistics to be less interesting — it dealt with realms of inquiry beyond her interests or goals. In short, a too-heavy focus on application has made previous math classes less applicable to her (in her mind), because the application has usually been focused on how mathematics would be used in careers such as engineering or accounting — careers she has no interest in. As a consequence, she struggled in the course to understand the contexts in which the algorithms she was learning are useful.

Prior to her meetings with me to explore her data, her strategy was to, in a sense, “get by” while minimizing the damage, to weather the storm and make sure that she does
not goof up so much that the storm is prolonged (e.g., “I’ll just push my way through and make sure that I do well enough that I don't have to re-take classes”). This strategy changed, however, as we began to meet and explore her data. Our meetings together served as a focus point for her to contextualize what she was learning in applications that were relevant to her; after this point, practicing statistics using self-data became her strategy for making sense of the material she was learning in the course. Again, the focal point for this shift took place during and following our second data exploration meeting.

At the end of the that meeting, the following conversation took place:

Jeff: Do you have any more questions?

Sara: No. That was cool.

Jeff: Why was that cool?

Sara: Cause I actually got to use what I learned.

Jeff: Had you not been able to use it before?

Sara: No, not for this class. (Second data exploration meeting, August 5, 2015, 01:02:10)

In addition, she decided at that point that she wanted to meet and practice correlation with her data later that day, instead of the next week. Based on my coding, I believe that this is because she started to see our meetings together as a strategy for understanding the material. Later that day, at the very beginning of the third data exploration meeting, she said:

Sarah: I like this. It’s interesting to actually use that stuff. I called my mom and was like, “Mom, guess what? I understand stuff!” (Sarah, third data exploration meeting, August 5, 2015, 00:02:05)
This is significant: she “likes” this (exploring her data and using statistics) — a steep contrast from her earlier statement, “I’m not a big fan of statistics” (Sarah, initial interview, 00:01:05). And her excitement after the second data exploration meeting was so great that she called her mother and excitedly told her that she finally understands what she is learning in class. We have no data on how often she normally calls her mother and discusses her academic activities, but we do know that she lives at home with her mother, and would likely see and talk with her that very evening. In short, this phone call may be an indicator of a significant realization on her part; that statistics could be useful and interesting, rather than frustrating drudgery. I do not believe it is because I explained anything differently to her during our meeting; rather, it was because our activities provided a context in which she could apply what she was learning to ask questions that are relevant to her life. Here are some examples of statements that she made in the final interview that supports this narrative:

523  [P]articipating in the study helped me a lot in my stats class. Just applying what we were learning (Sarah, final interview, September 2, 2015, 00:02:48).

525  [S]eeing how I could apply it to me, with tracking stuff, that was cool. It wasn't some random application, it was personal. (Sarah, final interview, September 2, 2015, 00:05:55)

These statements reveal that the “epiphany” moment related to her realization of how statistics could be useful in a context outside of a statistics course (and the examples normally used in statistics courses). While I do not have conclusive evidence of this, I believe that one of the focal moments of this epiphany took place towards the middle of the second data exploration meeting (quoted already in lines 176-184, in Chapter 5), where she was looking at two means that were different, but also close together
(comparing her weekend steps with her weekday steps). She said, “But it’s pretty close. 200 steps isn’t that much different… but we can use a hypothesis test to see if it’s significant!” (Second data exploration meeting, August 5, 2015, 00:18:20). At this moment, she realized that hypothesis testing could help her to see whether two means that are close — and thus where differences could be due to random variation — are yet far enough apart to draw conclusions about their underlying populations. In addition, consider the following exchange:

Sara: Well I was tracking my different things, but I didn't really look at it to make any sort of deductions or whatever. So when we met, we took that and we actually used it, and it was stuff I’d actually learned, so it was cool to be like "Oh my gosh, this actually applies to me." So, yeah.

Jeff: Huh, that makes sense. When you say applies to you, what do you mean by that?

Sara: It's real life: You can use it for real life situations, not just for problems out of the textbook. You can do it with stuff that is relevant. (Final interview, August 5, 2015, 00:04:04)

Each of these examples illustrate how using self-data and participating in this study served to change the way that she saw statistics; she no longer saw it as the same obstacle that she once did. The final interview took place during the second week of the new semester. Sarah explained, “So I'm taking two stat classes this semester, and I know that it does have a real world application, so it's easier to work on it and learn the stuff that we're learning” (Sarah, final interview, September 2, 2015, 00:05:07). In short, she was remembering what we had done during our data exploration meetings to help contextualize how what she was learning in her new courses might be useful in real-world contexts. When I asked her how these courses were going, she replied, “Good. I
actually understand stuff, it’s great!” The emotional tone of her reaction reveals surprise, a contradiction of her expectations. When I asked why, she went on to explain:

But it was interesting, because the stuff that we did in here made it more concrete in my mind. I understood stuff better than just learning it online through videos or through reading. It was good to actually use it, and it helped me to understand it better. (Sarah, final interview, September 2, 2015, 00:07:20)

During the final interview, I wanted to better understand better this shift in perspective, and so I asked for some more details; particularly, I wanted to make sure that she was not telling me what she thought I wanted to hear. The following exchange details her shift in attitude:

Jeff: Ok. And that's interesting. I'm going to go forward. You said before that you don't like statistics as much because it was more application based.

Sara: Because you use it in situations where it's not applicable to me. I'm never going to do a drug study, and I’m never going to do stuff like that because I’m going to be a teacher, so that wasn't really applicable. But I guess seeing how I could apply it to me, with tracking stuff, that was cool. It wasn't some random application, it was personal. …

Jeff: It's interesting to me, because the way you described it before, you liked the more abstract part of math better.

Sara: Yeah.

Jeff: So the implications, when we first had the interview, it was that you prefer abstract math, and you're not quite as interested in real-world math.

Sara: Right. And that's still true. I still...

Jeff: And it's fine if it's not.

Sara: ...like math science, like the math side of it more, out of math and statistics, but I've gained a greater appreciation for statistics through this. (Final interview, September 2, 2015, 00:05:39)

She clearly states here that, even though she maintains a preference for abstract math, she no longer holds the negative attitude that she once had towards statistics. Once
again, she attributes this shift in perspective to her participation in the study, and the personal applications made available to her through using her self-data. In summary, Sarah’s narrative one in which her anxieties and dislike towards statistics loosened as she came to practice statistics in a context that was more personally meaningful to her than the examples and exercises provided by her instructor. Statistics ceases to be the same obstacle that it was before; while it still might be necessary for her degree, she no longer views it as an exercise without any use beyond passing her course, nor does she see it as the drudgery she did before.

**Concernful Involvement.** As articulated earlier, how a phenomenon discloses itself to an individual depends in great part on what matters to them as they engage with the world. A correlation coefficient, for example, will disclose itself very different to a medical research than it might to an undergraduate statistics learner. In the former case, the correlation coefficient may be disclosed as a way of saving lives, an indicator of a possible life-saving drug, or something similar; in the latter case, it may be disclosed as a way of passing an exam. Drawing insights from situated learning, the learner’s involvement within a community of practice influences a great deal what matters to learners, and how things are disclosed to them.

At the beginning of Sarah’s story, what mattered to her was clearly passing her course; completing her homework was seen as an essential prerequisite to passing her course, and calculating $p$-values was seen as just that: completing homework. The process of calculating a $p$ value and comparing means between samples was, for Sarah, a matter of applying the correct algorithm and submitting the correct answers. This was, in
fact, expressed directly by Sarah during her final interview, when talking about the data analysis exercises that were provided by the teacher. She could not even remember, a couple weeks after the semester ended, what those data analysis exercises were even about. When I asked why, Sarah explained: “Because it didn't apply to me, it's just like ‘I have to do this, and get the right answer, so that I can move on.’” Later, she explained further, “I don't know, I felt like I was just doing it to get a good grade in the class, so it wasn't anything I was super interested in” (Final interview, September 2, 2015, 00:09:17; 00:09:45).

In short, she was engaged in the practices of the community of students; getting the correct answers was a means for moving her from greater to lesser peripheralness within the community of students, and ultimately a way for her to get a good grade and to move on to more advanced courses. The ultimate objective, in her mind, was to eventually complete her degree and leave behind her any need for calculating a $p$ value, since — as she expressly stated during our conversations earlier in the study — calculating $p$ values, and many other statistical activities, were not part of the practice of teaching college math (or, at least, the college math courses she hoped to teach). Sarah explained to me the conditions under which learning statistics might matter more (or differently): “It's stuff that... if you use statistics, then the answers you get will matter. But when you're just practicing or just taking a class on statistics, it doesn't really matter” (Final interview, September 2, 2015, 00:10:13).

That is, learning statistics did not matter beyond its usefulness in advancing the aims and objectives of Sarah-the-student; she explains further, “[I]f you were actually
doing that for a job, then that would be interesting. But for me it's like 'I don't care about this.' If I get the right answer, that's great, but... I don't know” (Final interview, September 2, 2015, 00:10:54). To clarify, Sarah made each of these statements during her final interview; the context she is describing is her homework in the course, in which she was using data sets provided by the instructor. Those data sets were intended by the instructor, Sarah implied, to represent the sorts of data sets that might be used by researchers in real-world scenarios. However, “[W]hen it's real life situations, it's hard because it's supposed to matter but it doesn’t,” again, as Sarah had explained, because none of those ‘real life situations’ exist in Sarah’s projections of her own future (Final interview, September 2, 2015, 00:10:13).

In contrast, the data that Sarah collected about herself seemed to offer another mode of concernful involvement — one in which calculating a $p$ value was no longer a means of getting the right answer on an assignment so that we can “move on.” As described earlier, when comparing her step totals on weekends with her step totals on weekdays, hypothesis testing disclosed itself as a way to see whether two means that are close — and thus where differences could be due to random variation — are yet far enough apart to be meaningful. That is, the act of calculating a $p$ value disclosed itself as an instrument of inquiry, a useful tool for exploring data and understanding something about our lives and our world. What made this crucial difference, in which the actions were no longer school assignments, and instead something more? Sarah believed that the difference was because the application was more personal, related to herself; she believed that it was the fact that an application was demonstrated that was not foreign to her (as
many engineering, medical, and other research applications had been so far in the course). As she believed, the crucial difference was that she realized, “You can use it for real life situations, not just for problems out of the textbook. You can do it with stuff that is relevant” — i.e., relevant to her (Sarah, final interview, September 2, 2015, 00:04:39).

What is interesting about Sarah’s story is that her interviews revealed a secondary objective, one that was not salient enough to fit into the broader narrative described above (but which could be thought of as a “sub-plot” in her larger story): remaining fit. She says, for example, “Well, I started going running half-way through the summer, and because of health reasons I haven't been able to the past two and a half years, so it was like ‘Yes, I can finally work on my fitness’” (Sarah, final interview, September 2, 2015, 00:29:04). Even more directly, she says, “[Tracking my steps] helped me to reach the goals I was setting for myself. Everyone says that you should take 10,000 steps a day, and I tried to reach that” (Sarah, final interview, September 2, 2015, 00:32:30). This goal is separate and distinct from passing her class, and her self-tracking seems to have helped advance her goal (if we take her report at face value). For example, while tracking her steps, Sarah would sometimes make excuses for physical activity. She explained, “And when I actually had something that was tracking it, then it was, ‘Oh, I should take my dog for a walk,’ or ‘Oh, I should go for a run,’ to try and get more steps, so then I could be healthier I guess” (Sarah, final interview, September 2, 2015, 00:32:40).

These little opportunities to engage in more physical activity were enabled, she believes, by the Fitbit device; the feedback offered by the Fitbit helps Sarah be more aware of her daily physical activity, and to thus more deliberately take time to increase
her daily step totals. For this reason, tracking her physical activities becomes a means to a
different end (than becoming a math teacher): remaining physically fit. This may be why,
when asked if she could continue self-tracking after the study concluded (and outside of
her courses), she replied that she would – at least, she would track her steps, sleep, and
heart rate, but not her mood. Her choice of continued tracking illustrates that she sees
tracking as serving a different goal: not to provide data to analyze and practice statistics
for her course, but as a way of promoting exercise.

The central question then becomes, did data analysis serve this secondary goal?
To some extent, yes, it did — and we can make a case that combining self-tracking with
statistical analysis problematized the familiar in a way that help disclose statistical
practices as an instrument of inquiry. Sarah had tracked her sleep during the year before
her participation in the study, but it was more a matter of routine, and she did not do
anything with the resulting data. She explains, “I was just like, ‘oh, that’s cool, I slept
less than I have in weeks,’ or ‘I slept a lot last night” (Sarah, final interview, September
2, 2015, 00:24:03). In other words, she was just making idle observations. But during the
study, she actually looked at the data and asked when (during the week) she slept the
most. “I’d never even looked at that,” she said. Aggregating her data by days of the week
introduced new questions that she had not even thought of asking.

She had a similar experience while tracking her steps. Before tracking her steps,
she explains, “I guess I never really thought, ‘Oh, I’m taking more steps today,’ or ‘Oh,
I’m not walking as much today’” (Sarah, final interview, September 2, 2015, 00:24:35).
But while tracking her steps, she was trying to “see if I could remember if something had
happened that had increased my steps or decreased it, like when I hurt my foot I didn’t walk around. Or if I went for a really long run, then it was more” (Sarah, final interview, September 2, 2015, 00:24:40). What we see in her comments here could be described as taking an aspect of her experience that is normally taken ready-to-hand, and making it present-at-hand, an object of study and inquiry; taking the “at-homeness” of her daily life and making it something to ask questions about, to interrogate. While the answers to these questions did not necessarily, advance her fitness goals, it did however provided a context in which statistical inquiry could be disclosed as a tool of interrogating the world (by examining and drawing conclusions based on data that cannot be drawn otherwise), rather than as a classroom exercise.

**Britney’s Narrative Arc**

This next narrative tells the story of Britney, a participant who already had a disciplinary investment that motivated her research; for Britney, the use of self-data provided a playground for practicing statistical concepts, but statistical analysis already mattered to her as an instrument of inquiry, and her learning was already fueled by a professional investment in her research. In this section, I will articulate a few elements of Britney’s story, and how each of these elements help us to better understand the possibilities that the use of self-data offered for her ongoing concernful involvement in her learning of statistics.

**Objectives.** Britney’s (then) current project at her work was to increase the retention rate of students at her university, by targeting interventions at learners who are at risk of dropping out. It is important to note here that, for a long time, Britney saw these
objectives as achievable entirely without statistics — she did not see data inquiry as an integral part of her profession. Rather, she saw her profession as a sort of people-oriented (rather than number-oriented) individual ministry; she saw her success as contingent on her skills with and interactions with people, not data. However, a series of very specific, recent experiences of Britney led her to adjust her view of the role that statistics might play in her profession. She and her colleagues observed a problem: “We had a bunch of students leaving [the university],” she explains, who did not need to be leaving (Britney, initial interview, May 13, 2015, 00:23:11). She and her colleagues explored the data they had available to them, which included student enrollment, course registration, grades, etc., and discovered that a large number of the students who were dropping out had failed one specific class.

As a result of this discovery, they were able to pay specific attention to learners who were struggling in that particular course, and Britney felt that this targeted intervention has dramatically reduced dropout rates. This experience demonstrated to Britney that large data sets, when smartly analyzed, could yield valuable information for her work as an academic advisor. Britney believed that if she could identify other at-risk groups to target, she would be able to find those students who most need help, the “edge cases” who are struggling. If she could identify these students, she explained, she could connect them with resources that they need to succeed. Now, Britney sees data collection and analysis as a very salient part of her job — she cannot imagine her future as an academic advisor without being able to use the tools of data analysis to help her to see where she should target her analysis activities. Her time is limited, she explained, so “I
want to make sure that I'm using my time wisely, and that I'm targeting the right groups of students” (Britney, initial interview, May 13, 2015, 00:12:14). For her, using data analysis to target at-risk students has become an essential feature of her identity as an academic advisor. Using data analysis to advance help target at-risk learners is the principle objective in her narrative.

She views her life as “pretty holistic” where her “hobbies, family, and work are all intertwined” — in her spare time, she finds herself thinking about better ways to reach and help students that she works with, or reading about counseling interventions that may help learners. For her, learning ways to better help students is not mere work, it is a life passion, and something that she thinks deeply, researches, and reads about even when not engaged in work-related activities. During the initial interview, Britney explained,

I'm really interested in making a difference in students' lives. I'm interested in higher-ed. So I'm a first-generation American; my dad graduated from college, but his life is very different than my uncles' and aunts', who didn't have access, or chose not to access higher-ed, so I think that what we do in higher-ed makes a big difference. (May 13, 2015, 00:03:38)

In other words, she self-identifies as someone who has been greatly benefited by university education, surrounded by those who have not been so fortunate (including members of her family as well as her community). For this reason, she explained, “I’m not like an 8-5 worker. My advising, we are helping people, it's more broad than that. It's not just showing up at work, and turning it off at 5. I'm really thinking, a lot of times that I'm not at work, about how to improve what I do” (Britney, initial interview, May 13,
There is a sense in which Britney has described herself as accomplishing precisely what Robert Frost poetically described: “My object in living is to unite My avocation and my vocation As my two eyes make one in sight” (Maxson, 1997). This was highlighted by Britney’s frequent references to her work during our data exploration meetings.

Obstacles/Conflicts. At work, Britney very large datasets on former and current USU students, in which she believes is hidden the information that will help her better target interventions toward at risk learners. She bases this belief on positive experiences in her past, and so projects similar successes into the future — if she can learn how to use statistics to analyze the data. However, she does not know how to do the analyses she wants to do. During the initial interview, she explained,

I took 1040 as an undergrad, and I took a social stats as an undergrad, and some sort of psych stats. But I really did the very minimum that I could to get by. I didn't understand the foundation... I don't have a good foundation. Even though I took the classes, I really just did the minimum to get by. (Britney, initial interview, May 13, 2015, 00:01:47).

This is a problem, she said, because “without that stat background, it's going to be really hard for me to [identify at risk students], and to do that effectively” (Britney, initial interview, May 13, 2015, 00:12:14). Britney hoped to recreate the success of her earlier intervention, but to do that she needed to learn the statistical skills necessary to analyze the large data sets at her disposal. During the initial interview, she explained that the statistics will help them ground their intuitions about what works and what does not work
in empirical terms: “[O]ur interventions we are doing are working, but it's all just
intuitive, and we are using raw numbers, and calculating things, very caveman-like, and I
really want to put a science to that” (Britney, initial interview, May 13, 2015, 00:01:12).

Further, Britney felt that although there were interventions in place that were
working, she had no way to empirically demonstrate their success. In addition, he had
been unable to explain in statistical terms to her contacts throughout the university why
her interventions work, something she had found necessary in her efforts to fundraise for
her department, and to justify her involvement in various academic programs. She
described her experience:

Sometimes when I’m talking to people across campus, and I'm talking about what
I'm doing, they ask me about some of these statistical terms, and I don't really
know what they are. It makes me feel a little inferior. I'm like "Oh. I know what
I'm doing matters, but I don't know how to talk about it.” …

Well I’ve been trying to get more money from departments, and so when I’m
telling them what we're doing and why it matters, they'll say "Well, tell me about
this, this, and this." And I’m like I don't even know... And they're like "Can you
put it in a trend line?" And I'm like "I don't even know what a trend line is!" So I
feel a little stupid, and I want to be able to talk about what I’m doing to
researchers, or with researchers. (Britney, initial interview, May 13, 2015,
00:24:16)

In short, in Britney’s narrative, her goal is to use statistics to target academic
interventions at at-risk learners, to thereby help students to find resources they need in
school; it is a goal that is informed by values and passions that extend beyond the
workplace. The central obstacle or conflict in Britney’s narrative is that she does not
understand statistics; she was negligent in her undergraduate and graduate years, and
simply did not learn the statistical practices that she now needs to serve learners and
advance her objectives. This obstacle fuels a sense of insecurity in Britney; she feels
unable to communicate with peers across campus and to use the language, rhetoric, and tools they ask of her in order to justify her ongoing involvement in their affairs.

**Plot/story.** It is at this point in Britney’s story that her supervisor encouraged her to take an undergraduate statistics course, as well as an experimental design course, in order to learn these needed skills. Britney decided to take an introductory statistics course during summer term, and to follow with an experimental design course during fall semester. She hoped that these two courses would, together, give her the basic skills that she needed to complete her analyses, develop more targeted interventions, and to empirically justify existing interventions with the data that she has already collected on students at the university. Since Britney did not have any sort of academic timeline, failing the course was not really a concern for her. However, during the initial interview, she said that “it matters 100%” to her that she actually learns the material in this course. “As an advisor,” Britney, explained, “the foundation piece is really important” (initial interview, May 13, 2015, 00:09:43). Even if she were to get an A, she said she would repeat the course again if she did not feel confident that she had adequately learned the material. She had already gotten good grades without learning the material in the past, but this time, she was taking the course to learn.

Britney saw participation in this study as a strategic maneuver in pursuit of these goals — *but not at first.* When she first joined the study during the first week of class, her primary motive was to help me as a researcher; Britney explicitly stated that she is not motivated by the compensation, and in fact offered to participate without compensation to demonstrate this (she was compensated regardless). She explained that she knows how
important it is to collect many data points when doing research, and wanted to contribute her own experiences to the research project, for my benefit as a researcher. She suspected that using her own data to practice statistics would help her understand statistical concepts or formulas better than she would if she just used other data with no context. She explains, “I feel like using my own data, or data about me, would help me understand the back, or the formulas, or how getting to this number, a little better than if we're just using examples from different disciplines.” However, she explicitly states that — at least at the beginning of the study — this was not her primary reason for participating.

Her primary reasons for participating shifted as the study progressed. During the initial interview and first data exploration meeting, her focus seemed to center on what would help me (as a researcher); she seemed eager to please me. During the second and third data exploration meeting, however, her focus seemed to shift, to center instead on what would help her as a researcher and academic advisor. This is evidenced by the questions she would ask, and statements she would make (and the language used in her statements). For example, during the initial interview, as I asked her about each option for her self-tracking, she replied, “Yeah, I’d be willing to help out with that too” (Britney, initial interview, May 13, 2015, 00:28:15). She saw her participation as helping me. She herself described this shift: “[A]t first I was like, you need help, he needs help, so I'll help. And then as we met and as we used my own data, it was actually helping me understand the material” (Britney, final interview, June 23, 2015, 00:07:48). In short, her participation in the study, and using and analyzing self-data, became a strategy for advancing her broader goals of becoming a better researcher and better targeting learners.
Not of all of the benefits she described related to self-data; for example, she realized that R programming was an invaluable tool for analyzing data about her students, and so she decided to master R programming. During the final interview, she explained:

569 A lot of the R knowledge, and some of the ins and outs I actually learned in our
570 sessions, so that was really good to watch you or have you explain the code to me.
571 I think that was probably a by-product of what we were doing, but to me, learning
572 the R was really helpful with you here. (Britney, final interview, June 23, 2015,
573 00:03:53)

In addition, the data exploration meetings seemed to help Britney understand statistical concepts when other tactics and strategies failed. For example, Britney struggled to understand the Central Limit Theorem, until I demonstrated the theorem for her using her own data during the first data exploration meeting. At the beginning of the second data exploration meeting, she mentioned how useful the demonstration was for her:

574 You wouldn’t believe how much I understand of the central limit theorem after I
575 left, after you ran [the demonstration]. … I sometimes have a hard time wrapping
576 my brain around how you have the mean of one sample, and then you have the
577 mean of a few of them, like 30 of them, and how that can make sense in the big
578 picture. (Britney, second exploration meeting, June 12, 2015, 00:02:45)

During the final interview, she described in more detail her frustrations with understand the Central Limit Theorem, and how the demonstration with her own data helped her:

579 I really had been working on that for a few days, and I really wasn't...I was
580 watching YouTube videos and it just wasn't clicking, but one good thing about
581 what we did together was me understanding that component of it, which was
582 really helpful. (Britney, final interview, June 23, 2015, 00:05:54).

Though her familiarity and comfort with statistics increased throughout the duration of the course and the study, Britney still did not feel confident in her statistical
ability. She “was expecting to catch on a little quicker to a lot of things,” but still feels that she “got out of it what [she] wanted to” (Britney, final interview, June 23, 2015, 00:25:51). Britney had previously analyzed the ACT scores of students to see if she could predict a “danger zone” for students, and after the study, she felt that she could use concepts like correlation and hypothesis tests to improve her results, and to answer more questions using data she has already available. Her primary purpose in taking the statistics course was to “learn how to use statistics to make decisions on how to advise students,” and during the final interview, she explained that using her self-data has helped her learn this because she “cared more in class or in homework about understanding the technique,” because her “own data was the application” (Britney, final interview, June 23, 2015, 00:53:20).

**Concernful Involvement.** During the data exploration meetings and interviews with Britney, I observed that while the use of “self-data” provided a context for learning statistics that engaged her as a learner, she seemed more interested in understanding how the things she was learning would help her as an advisor to advise students at the university. She would regularly make mention of how the things she was learning might help her in her professional capacity. While there are many examples, here is one that illustrates: early during the first data exploration meeting, I demonstrated to Britney how I used R programming to curate her heart rate data — and Brittney gave her rapt attention, indicated by sitting forward in her chair, nodding as I explained the syntax of the code, and occasionally stating, “That is so cool!” After explaining the syntax, I ran
several dozen lines of R code that retrieved her step and heart rate data from the Fitbit servers, and formatted the data for analysis. The following conversation then occurred:

Britney: Wow. So when I’m using this with students, and I have the same spreadsheets, and I take it out as a csv file, and I have that code, and if the spreadsheet’s the same every time…

Jeff: Yep. Especially if the format is the same every time, and you can have different data.

Britney: That’s so amazing… in less than a minute. So the time-consuming piece is writing the code. (Britney, first data exploration meeting, June 5, 2015, 00:05:54).

Notice that the first response from Britney was to say, “So when I’m using this with students…” Here, Britney demonstrated that she saw her work with students as an immediate application of the R skills that she was learning — learning R, in this context, seems to have little to do with pleasing the instructor of the course, passing her assignments, or pleasing me as a researcher; rather, she saw R as an instrument for empowering her work as an academic advisor, and for curating the data sets that she studies while trying to better target interventions at at-risk learners.

I argue that the use of self-data may indeed connect to the concerns and ongoing life projects of learners who do not otherwise have a disciplinary investment that motivates their statistics learning, and thereby show them how statistics can be used to advance their knowledge of the world — but Britney’s experiences demonstrate that having a disciplinary investment to begin with may offer a still superior mode of concernful involvement (superior, that is, from the perspective of inviting learners to be invested in what they are learning, and to see statistical tools as an instrument of inquiry). Britney’s concernful involvement — in which her concerns were for her students, and in
which statistics was a tool for helping her better serve her students — provided a context in which statistics (perhaps whether practiced with self-data or contrived data) was seen as far more than merely a way to get a good grade in a course.

In this way, Britney’s concernful involvement could be treated as a “best case scenario,” the benchmark that we want other learners to experience in their statistics learning. In Britney’s case, exploring her data may have been fruitful because it allowed Britney to leverage her personal familiarity with the data when trying to understand obscure concepts (like the central limit theorem) — but it was her professional investment as an academic advisor that made data analysis matter to her. The hope, however, is that the use of self-data might “plug into” the concerns of other learners who do not have this same professional investment (by virtue of being undergraduate students, perhaps), and invite them to step into a context where statistics “matter” to them in similar ways. (Similar in “kind,” perhaps, if not in degree — at minimum, we want statistics to be seen as something more than a tool for advancing or maintaining their status in a community of students.)

Other Participant Narratives

Of course, the narratives of other participants differed tremendously from Sarah’s or Britney’s — with different disciplinary interests and life experiences, they had different objectives and different conflicts in their narratives. I will not detail them here, except to note briefly how the narratives of the learners interfaced with their concernful involvement with statistics and self-data. Brian, for example, had a somewhat different story from either Sarah or Britney — for Brian, self-data did not seem to “work” at all (in
the same way that it did for the other participants) — at no point in the study did he truly develop an investment in data analysis, or anything surpassing what might be called “idle curiosity.” Brian participated in the study, he explained, because his prior experiences participating in research studies have been interesting. He also appreciates when others help him with research at his employment, so he wanted to return the favor. The compensation also served as a primary incentive for him.

At the time of the study, Brian was in the process of applying to graduate school, and presumes that he will pursue a graduate education in economics. However, he was unsure of his future plans. He had been doing research in economic policy for two years for his employer (an economic think tank), and felt a little weary of the subject. He planned at this point to continue studying economics and to "see where that takes me,” but was neither certain nor passionate in his choice of study. For Brian, not only is his professional future hazy and unclear, the relevance that statistical literacy will have in his future life is at best uncertain. After some prompting, Brian expressed the opinion that statistics are a good way of “formalizing” our ability to notice patterns and make value judgments — it’s a way of testing our assumptions empirically, to confirm or disconfirm our suspicions in a systematic way, bringing us from the world of ideas to the world of “real things.” However, his articulation of statistics as a valuable tool for empirical inquiry seemed perfunctory, expressed only after repeated prompting, and without the conviction of personal experience.

In short, Brian had none of the disciplinary investment that motivated Britney’s passion for learning, and all of Sarah’s initial ambivalence towards statistics. This would
in fact have been just the sort of context in which we hope that the use of self-data would supply additional reasons to care about statistics learning. However, this did not happen for Brian — in large part because he had no ongoing concerns or interests in any of the things options made available to track about his life. Though he chose to track his computer usage, he stated (on multiple occasions):

When I'm on my computer I'm either working or playing a game, which I don't see as a waste of time because it's recreation. (Brian, final interview, August 21, 2015, 00:17:09)

When I use [the computer], isn't as big of a deal, again by preference. I don't really beat myself up over computer usage. (Brian, final interview, August 21, 2015, 00:22:36)

In addition, though Brian chose to track his steps, he stated, “I don't think it was that important to me, again it was just more interesting. I don't really have a preference of how many steps I take either way.” When I asked him about the questions he asked about his steps, he stated, “I don't really care about them. It's not that important to me if I’ve taken this many steps” (Brian, final interview, August 21, 2015, 00:25:19). More examples were discussed in Chapter 6. These examples highlight a theme in Brian’s narrative: with no conflict to overcome, no troubles or difficulties with the statistics course or its content, his participation in the study and self-data analysis served him as little more than a way to satisfy an occasional idle curiosity and to obtain compensation for his time. Unlike other participants, it did not position data analysis as anything more than something he does to please the teacher or — in the case of self-data — the researcher (myself).
The narratives of other participants could be described as existing on a spectrum between Sarah’s experiences and Brian’s experiences. None of the other participants experienced a transformative change of attitude as Sarah did — but unlike Brian, the use of self-data did offer moments in which statistics was disclosed to them as an instrument of inquiry. At the time of this study, for example, Peter was nearly finished with his degree in Nutrition Science, and hoped to enter medical school after he graduates. Although he originally pursued an engineering degree, he gravitated towards the medical field because of a stated desire to help people. He expects to find work as a medical professional fulfilling (as well as high-paying — an important consideration, he explained, when providing for his future family). Like Brian, Peter struggled to articulate more than a vague idea of how statistics would be useful to him in his professional pursuits.

However, the use of self-data offered for Peter a context in which he could use statistics to illuminate something about his personal life. For example, he explored his sleep habits using the $t$ test, correlation, and regression. Afterwards, he wanted to know what kinds of activities — such as computer and phone usage, or his daily steps — might influence his sleep duration and quality. In addition, he explained, “What I cared about most was why. Why I couldn't sleep, and what could be related to that. So I looked at the aspects in my life that were… the only aspects I knew that were related, that could be related” (Peter, final interview, June 24, 2015, 00:27:33). He knew that these tools could help answer those questions, even if he did not have the data he needed to obtain the
answers. He saw those statistical tools as something that — with more data — could advance his understanding of sleep habits that he wanted to change.

As detailed in Chapter 6, Kristen, Chris, and Greg had similar experiences, in which the use of self-data disclosed statistics as more than a mere classroom exercise. They had varying ideas for how statistics would factor into their projected futures:

Kristen had a fairly concrete vision of how statistics would play into her future professional life, for example; in contrast, Greg could articulate no vision for how statistics would ever be useful to him. For this reason, Kristen statistics disclosed itself to Kristen as a means of preparing her for her future career, while statistics did no such thing for Greg. For Greg, statistics was simply a required course, and statistical practices were things he must master only to the extent required to pass the test and get a grade. But for both participants, the use of self-data provided a context in which statistics could be seen as something more, as a tool for exploring their own personal world.
CHAPTER VIII
DISCUSSION AND CONCLUSION

In this final chapter, I will begin by briefly summarizing the findings of the previous three chapters. Then, I will present some additional discussion of the findings of the previous three chapters, and how those findings interface with the broader literature and my research questions. Then, before concluding, I will explore some potential directions for future research.

Summary of Findings

The principle purpose of this study was to (1) explore the conditions under which self-data can help data analysis matter to learners in an undergraduate context, and (2) to explore the possibilities for concernful involvement in data analysis made possible by self-data. This is important because undergraduate learners often approach statistics learning with a sense of dread (Cruise, Cash, & Bolton, 1985), experience statistics learning as painful (Rosenthal, 1992), and treat statistics learning as an obstacle to overcome, rather than as a valuable instrument of inquiry (Roberts & Bilderback, 1980; Bradstreet, 1996); this is in large part because they fail to see the immediate relevance of statistics in their anticipated personal and professional lives (see, e.g., Kirk, 2002).

Some have argued that this is in part because the data that learners are tasked with analyzing is far removed from contexts of personal or professional relevance, but is often contrived (see, for example, Greer, 2000; Singer & Willett, 1990). The suggestion has been made that instructors should provide learners with opportunities for data creation
(Hancock, Kaput, and Goldsmith, 1992), and involve learners in analysis of data sets that are large, real, messy, and relevant to their personal or professional interests (Singer and Willett, 1990). The hope is that the use of self-data can help meet these recommendations in a way that helps involve learners in data analysis as instruments of inquiry (rather than as mere classroom exercises to be completed and forgotten about), illuminating something about their personal world that is of interest or concern to them, and this exploratory study was launched to investigate whether (and the conditions under which) this can happen.

**Conditions for Mattering.** To discover the conditions under which self-data analysis mattered to learners, I went through multiple stages of coding of interviews with the participants, and of their data exploration meetings – starting with a more open initial coding, and complementing it with a more directed, axial coding process. Using the resulting coding scheme, I noted five themes in the experiences of the learners that hint at the conditions under which data analysis can be made to matter to them (the results of this analysis are presented in Chapter 6):

1. Learners cared more when they could form expectations of the data. When learners had no intuitions (even grossly mistaken intuitions) about what the data would show (such as, for example, imaginary hotdogs, or their breathing rate), they cared less about the analysis. In addition, external benchmarks helped learners form expectations of their data (e.g., the common knowledge that active individuals walk 10,000 steps a day).

2. Learners were more engaged when there was variability in the data. Data with little variability simply did not offer learners the opportunity to interrogate the data or to
concern themselves with the data analysis (for example, when an individual’s heart rate did not fluctuate much throughout the day).

(3) Learners cared more about their analyses when the data took on a moral valence to the learners. Learners who simply did not see the ups and downs of the data as being more or less preferable did not find the data analysis to be meaningful to them. External benchmarks can also help learners form intuitions in this regard (again, the externally supplied goal of achieving 10,000 steps a day helped learners to interpret their data sets).

(4) Learners cared more when they tracked data and asked questions that related to existing, ongoing concerns; for example, when a participant was already concerned about their computer usage, or their sleep patterns, they found that data analysis related to those concerns mattered more to them. However, even when the potential was there, this did not happen automatically. Instructor-guided questions can help plug self-data into ongoing concerns of learners.

(5) Learners cared more when they could investigate potential covariates of their data — for example, when learners could track and analysis their sleep and their computer usage, or their heart rate and their mood, etc. When tracking variables in isolation, learners could rarely address or investigate most of the questions they formulated about their data.

**Concernful Involvement.** Finally, I explored the narrative experiences of a few of the participants, to understand the ways in which using self-data invited them to be concernfully involved in data analysis. As described earlier, concernful involvement
describes the comportment a learner has with respect to their activities; e.g., one can be involved in data analysis as a homework assignment or as a means of exploring the world – or both – depending on what concerns the learner as they engage with the practices at hand. Since I was interested in exploring whether self-data helps learners to see statistics as something that matters beyond the classroom, learning as embodied familiarization (with its construct of concernful involvement, see Yanchar, Spackman, and Faulconer, 2013), coupled with significant insights from situated learning, offered useful vocabulary to frame and address my research questions.

One participant (Sarah), for example, saw statistics as an obstacle to her degree, and something without real application in her future professional life (see Chapter 7 for this and the following examples). The use of self-data, however, offered her a context in which statistics could be used as an instrument of inquiry (in the present), rather than as a mere homework assignment. This dramatically changed her comportment and attitude towards statistics. Another participant (Britney) demonstrated precisely the type of concernful involvement we hope to see among statistics learners — because of her ongoing professional projects, she saw statistics as a valuable tool for advancing her professional concerns and ongoing research questions. A third participant’s (Brian) total ambivalence towards the tracked data resulted in a narrative in which self-data did not invite the learner into new concernful involvement with data analysis — from the beginning to the end of the study, his concernful involvement was as a participant in a research study, performing activities requisite to earn his compensation.
In conclusion, the use of self-data in this study helped several of the participants better grasp the potential relevance of statistics in the practical activities of their anticipated personal and professional lives. Learners in the study, while exploring self-data using statistics, began to see statistics as potentially useful in ways that they previously did not — and in a couple cases, this helped to dramatically decrease learner’s expressed anxieties towards statistics. (While anxiety was not measured in this study in any canonical sense, it can be argued that Sarah’s narrative, for example, demonstrates a decreased fear of statistics.)

For this reason, the use of self-data may very well be a vitally useful tool for addressing the concerns expressed by Kirk (2002), who noted that students struggled to see the relevance of statistics, as well as the concerns expressed by Rosenthal (1992), who noted that statistics is often a dreaded and painful course in an undergraduate’s curriculum. Researchers have observed that this prevalent negative attitude towards statistics may be due in part to the fact that learners do not see the immediate relevance of what they are learner (Cruise, et al., 1985; Roberts & Bilderback, 1980). The use of self-data, in this study, help learners to do just that, by connecting data analysis to existing, ongoing concerns (and for at least some learners, creating new opportunities for concern).

Not only does the use of self-data involve statistics learners in the formation of statistical research questions and data creation encouraged by Hancock, Kaput, and Goldsmith (1992), and the resulting data set can readily meet each of the recommendations made by Singer and Willett (1990): it is raw, authentic, familiar to the learners, personally relevant to learners, and (can) be amenable to multiple forms of
analysis and (can) afford genuine opportunities for new knowledge. (The latter two depend on the data that is gathered and other practical considerations.) This shows great promise in helping learners to care more about data analysis, and I hope that future research will explore the practical feasibility of an implementation of self-data to help undergraduate learners in a broader classroom context.

Discussion

Of course, “mattering” is an intrinsically subjective phenomenon that cannot be isolated from an individual’s history, present social contexts and life projects, and future ambitions and aspirations, and for this reason, every learner’s experience with the self-data was different. As described above, however, I did observe some important commonalities; the experiences of learners, though each unique in their prior interests and concerns, their expectations for the future, their engagement with the research study and with statistics learning, and so forth, did hint at similarities that helped reveal the themes outlined in Chapter 6. In this study, I attempted to walk the delicate tension between studying the subjectivity of each learner’s experiences and studying the commonalities between their experiences. This can be seen in the themes outlined in Chapter 6 and the narratives illustrated in Chapter 7.

In addition to the themes in Chapter 6, all of the learners felt that the use of self-data was more engaging and interesting than the use of contrived data sets when practicing and learning statistics. Those who mentioned or described the data analyses they performed in class (with data provided by the instructor) described those analyses as
immensely less meaningful, or more “trivial,” or any number of other descriptors, when compared with looking at their data about themselves. So on a subjective level, participants expressed a belief that the data analysis mattered more to them when they were analyzing data about themselves than when they analyzed data that had been provided by their instructors. Evidence from the coded interviews and data explorations meetings suggest that, though self-data analysis mattered more to some participants than others, learners generally demonstrated a clear, elevated interest in the data they collected about themselves. They were able to recall aspects of the data and their analysis of the data in greater detail than they could recall aspects of the data provided by their instructors. They could discuss in some detail how the data related to them and their lives. And they seemed to see ways in which statistical concepts and practices — such as a t-test, or a correlation coefficient, etc. — could tell them more about their themselves than they could learn merely by looking at the data provided by the Fitbit dashboard, which demonstrates an immediate perceived relevance of statistics that has been missing in much of statistics instruction (Kirk, 2002, Gal & Ginsburg, 1994).

**Not about personal vanity**

A central insight gained from analyzing the experiences of participants in this study was that the best use case for self-data is not about appealing the vanity of learners, or even their innate interests in their selves (something which I suspected but had no empirical evidence for); data analysis about the self did not matter to learners in the study in a number of instances. Rather, data analysis mattered to learners in contexts where learners engaged in data analysis with a concernful involvement that mirrored (in at least
some important respects) the concernful involvement of disciplinary professionals. Professionals usually have a deep familiarity with the data they analyze, as they are often involved in the formation of the research questions and the data collection. This familiarity informs expectations about the data, and helps them to generate hypotheses to test in their analysis. They are also generally familiar with the prior research in their area of interest, which helps them form benchmarks against which to compare the results of their analysis, and their research questions are often informed by longstanding research interests. I would argue that it is intuitively understanding precisely these aspects of a professional’s invested engagement with research that led Singer and Willett (1990) to suggest that data in the classroom be raw, authentic, include great detail about the sampling, instruments, and purpose of the research, and be of personal interest and familiar to the learners.

To clarify, I do not expect the use of self-data to eliminate a learner’s concernful involvement as a student in a classroom, where they care about the analyses at least partly because of the requirements of the teacher and their need for a good grade; participants in this study still expressed such concerns as part of their reasons for practicing and learning statistics. The hope, however, is to introduce new forms of concernful involvement in addition to those typical of a student. And this study demonstrates that using self-data can help at least some learners adopt a similar form of concernful involvement to that of disciplinary professionals, by inviting learners to analyze data that they are deeply familiar with, and about which they can therefore form expectations and hypotheses.
(which can form the basis for sense-making about the data and the results of their analysis).

In addition, the use of self-data can invite learners to participate in analyses that address ongoing concerns or life projects of the learner. Britney, for example, had multiple ongoing projects and concerns that became relevant in this study: first, she was deeply concerned about the students she served as an academic advisor, and second, she was concerned about her knee and her general health. Learning statistics was already seen as useful in addressing the first; the use of self-data helped statistics become useful in addressing the second. This example is one of several that illustrate how self-data can plug statistics into ongoing concerns and interests.

Additionally, while not quite as salient in the experiences of the learners as I expected (or had hoped), the use of self-data can potentially open up new possibilities for concern. As described in my theoretical orientation, for example, that which is mundane and familiar (such as one’s sleep habits) can be rendered unfamiliar with closer scrutiny (through the use of a Fitbit device, for example), and new possibilities for concern may arise in that context. In this way, problematizing the familiar — perhaps literally rendered as “creating or encountering problems with what was once familiar or mundane” — could not just plug statistics into ongoing concerns (which requires learners to have ongoing concerns related to aspects of their lives that they track), but create new opportunities for concern. Again, while not quite as salient as I would have hoped, there were some examples of this in the experiences of learners in the study. As described in Chapter 7, tracking her steps and her sleep helped Sarah step into new fitness concerns.
that had not been a focus prior to this study. Conversely, though, examining his steps, sleep, and computer usage did not successfully invite Brian into new concerns — his prior apathy towards those aspects of his life wholly survived the closer scrutiny supplied by self-data. In this sense, the creation of new concerns for learners was a bag of mixed success.

Some Limitations and Alternative interpretations

One potential weakness of this study is that some confounding influences on the learners’ concernful involvement with self-data exist. It is difficult to parse out what aspects of the participants’ experiences and concernful involvement (if any) may be due to the fact that the learners were participating in the study outside of the classroom environment, and were thus not subject to all of the concerns (within the context of the research study) that they might be subject to if they were using self-data in an actual classroom environment. In other words, when exploring self-data as part of this research study, none of their activities contributed to their grades in the course (except indirectly), nor were the activities of self-data analysis necessary for passing their course. So it is expected that learners would be concernfully involved with analyzing self-data in ways beyond those typical of a student; that such was the case is thus entirely unsurprising.

This was known at the commencement of the study; given that my interest was in understanding the individual experiences and narratives of learners who explore self-data in a statistics learning context, it was not essential that I mimic in every respect the conditions of a classroom (with all the concerns that come with it). I did not expect that participants in the study be concernfully involved in the study for the sake of earning a
grade or pleasing a teacher, since none of the activities directly contributed to those aims. My research questions and methods were framed so that I could explore what other forms of concernful involvement are made possible by self-data (beyond those typical of students), and the conditions under which self-data mattered to learners (or “plugged into” their ongoing life projects and concerns).

However, it was possible that learners might be involved in the activities of the study so that they can better perform in the course; that is, it was possible for participants to be involved in the study as a means of indirectly addressing their concerns as students. I was therefore open to that narrative as a possibility, and there were hints of this narrative in the experiences of Sarah (see Chapter 7), who discovered that participating in the study dramatically improved her understanding of the relevance of statistics and therefore her attitude towards the activities of the class. I did not see a lot of evidence for this narrative in the experiences of other participants; while they found value in participating in the study, there was little evidence that they felt it consequentially impacted their success in the course.

In addition, as designed, this study simply could not address or explore the learning of the participants, since there was simply no way to separate the influences of using self-data from the influence of multiple meetings with and personal tutor-like attention from a more knowledgeable other; for this reason, this study tabled all questions related to learning and focused entirely on the topic of mattering, which could only be explored subjectively. However, even so, the potential confounding influence of personal tutoring cannot be ignored; it is entirely possible that the concernful involvement of the
learners was sensitive not only to the analysis of self-data (and the questions being asked of the data), but also by the personal attentions of the researcher (myself). As a quasi-tutor in the context of this study, the questions I asked – even from the initial interview, where I focused their attention on their motives for participating in the study, the possible concerns and life projects that are relevant to their self-data collection and analysis, etc. – may have influenced their perceptions of the relevance of statistics in their projected personal and professional futures, as well as their concernful involvement in data analysis, in addition to the use of self-data. Each of these limitations were acknowledged from the outset of the study; the design of the study was chosen carefully to help illuminate the narratives of the learners, and I argue that despite these limitations, this study yielded fruitful analyses into the concernful involvement of learners using self-data in a statistics learning context.

Suggestions for Future Research

This study focused on the individual, qualitative experiences of learners with self-data in an undergraduate context, and hints at some promising possibilities for how self-data can be leveraged to help learners see data analysis as mattering to them. I believe that future studies could explore these possibilities some more, including: (1) extending the research into more authentic classroom contexts (addressing issues of scalability), (2) exploring the opportunities for concernful involvement offered by self-data to learners of different demographics (specifically, younger learners and learners in STEM-related disciplines – science, technology, engineering, and mathematics), and (3) including
additional quantitative measures (to complement the qualitative experiences explored in this study).

This study involved the exploration of self-data in a way that involved minimal effort from the participants; prior to data exploration meetings, I downloaded their data from the Fitbit web app, engaged in extensive cleansing and manipulation using R to make the data ready for the specific analyses the learner might want to conduct, and guided learners through those analyses in a one-on-one environment. This process, from beginning to end, is simply unlikely to be scalable to a broader classroom environment. To use self-data in the classroom, an instructor may rely much more heavily on the students to download and curate their data, and to properly prepare it for analysis. In addition, students may not have access to one-on-one attention as they analyze their data — thus leaving them up to their own devices (or each other) when they need assistance due to unexpected analytical hiccups, which naturally occur in raw, non-preprocessed, large datasets.

An argument can be made that this may in fact be an advantage in a learning context, given the fact that real-world research in a professional context often involves the collection and curation of large, messy datasets — the classroom recommendations of Cobb and Moore (1997), Singer and Willett’s (1990), Hancock, Kaput, and Goldsmith (1992) are premised on the fact that preprocessed data may in fact deprive learners of the learning opportunities afforded by real, raw, large, and messy data. The issue at hand, however, is one of classroom management, and whether or not learners will be able to navigate and analyze such data sets without more supervision than an instructor can
provide. Research should be done to explore the implementation of a self-data statistics curriculum in a classroom context, to explore the practical necessities and limitations, as well as the scalability, of such an intervention. It may be that a multiple-iteration design-based research study would be well suited to such an endeavor.

In addition, this study focused entirely on the experiences of learners analyzing data about their own personal activities — but this does not exhaust the possibilities of self-data. Self-data can be involved in and part of a larger data set, such as data collected by a classroom community, and aggregated into a single data set. In fact, such forms of collective self-data — data that many learners might gather about themselves — might provide many more possibilities for analysis and different possibilities for concernful involvement. Such an implementation was explored by Lee, et al. (2016) in an elementary statistics setting, in which statistics learners participated in self-data projects that aggregated the experiences of multiple learners (referred to in the study as “quantified selves,” as opposed to the “quantified self”). For example, learners in the study used Fitbit activity trackers to compared the recess activities of multiple students engaging in two different recess activities (“Capture the Flag” vs. “Ball Tag”) using histograms and boxplots, as well as measures of center and spread, to determine which activity was the most active.

Further, I believe that it would be fruitful to explore how concernful involvement with self-data changes over time, and whether the concernful involvement of younger learners with statistics and self-data analysis differs from that of undergraduate learners, and also whether there are differences amongst graduate learners (who are ostensibly far
more likely to see the relevance of statistics in their anticipated professional lives, and more proximate to communities of researchers that use statistics on a regular basis), as well as experienced professionals. In addition, I think it could be fruitful to explore possible differences in the experiences of STEM learners and non-STEM learners with self-data, and how the expectation of a future in a STEM profession (which are ostensibly more likely to involve mathematics and statistical practices than non-STEM professions) interacts with the concernful involvement of learners exploring self-data using statistics.

Finally, I focused this study on the narrative-based exploration of the experiences of individual learners, investigated what mattered to them (in relation to their anticipated personal and professional futures). While this analysis was fruitful and illuminating, other work highlights additional constructs that may yield fruitful and interesting analyses. For example, Cruise, et al. (1985), Onwuegbuzie, et al. (1997), Perepiczka, et al. (2011), and others have explored the construct of anxiety in statistics learning, from both quantitative and phenomenological points of view, and have constructed validated measures of statistics anxiety (see Cruise, et al., 1985) that might be useful as a future complement to the qualitative analyses of this study. Such instruments may be useful when exploring the possible scalability of self-data interventions in a larger classroom context, where the qualitative approach used in this study would quickly become unwieldy (if the experiences more than a handful of students are analyzed), and could therefore fruitfully be fortified by the pre- and post-test results of a brief, quantitative instrument.
References


http://works.bepress.com/victor_lee/22/

Lee, V. R., Drake, J., Cain, R., & Thayne, J. (2015). Opportunistic uses of the traditional school day through student examination of Fitbit activity tracker data. In M. U.


factors in computing systems (pp. 1163-1172). New York, USA: ACM. doi: 10.1145/2556288.2557039


Appendix A: Recruitment Email

[Student name],

I see that you are registered to take Statistics 3000 this summer with Dr. Kady Schneiter. My name is Jeffrey Thayne, and I am a PhD student in the Instructional Technology and Learning Sciences program. I am currently conducting a dissertation study related to statistics learning, and I would like to invite you to participate in the study.

Many students and non-students alike track elements of their daily lives. Some people, for example, wear fitness trackers and pedometers to measure their daily physical activities. Others track how much time they spend on their phone, or their computer. Some track their daily mood swings, or their weight. All of these are part of a growing Quantified Self movement, and yield large amounts of valuable, personally relevant data to users. We think that this data can be leveraged in statistics learning.

If you choose to participate in this study, we will invite you to track two elements of your daily life or activities. We will provide you with the tools that you need to do so. We will also invite you to meet with me 3 times during the course, to explore the data you collect using some of the statistical concepts and practices you learn during your course. We will also interview you before the start of the course, and again at the end of the course, with a brief followup over the phone each week during the course.

The benefits of participating in the study include 3 hours of individualized attention while interacting with data using statistical measures (which can be thought of as individualized tutoring sessions), and an increased exposure to the concepts you are
learning in the course. There will also be monetary compensation for participating ($100). If you wish to participate, please visit the following link, which contains more information and will allow you to register your interest in the study: [insert link here]

Many thanks,

Jeffrey Thayne
Appendix B: QSIA (Online Form)

Here are screenshots of the QSIA survey that participants were directed to in the recruitment email:

Many students and non-students alike track elements of their daily lives. Some people, for example, wear fitness trackers and pedometers to measure their daily physical activities. Others track how much time they spend on their phone, or their computer. Some track their daily mood swings, or their weight. All of these are part of a growing Quantified Self movement, and yield large amounts of valuable, personally relevant data to users. We think that this data can be leveraged in statistics learning.

To participate in this study, you will be invited to:
1. Track two elements of your daily life or activities, found in the list below. We will provide you with the tools that you need to do so.
2. Meet with the researcher on 3 separate occasions to explore the data you collect using the statistical concepts and practices you are learning in the course. These meetings will take place around Week 3, Week 5, and Week 6 of the course.
3. Participate in two interviews, one right before the course starts (or during the first week of the course), and the second during the last week of the course (or right after it ends). You will also participate in a brief, 5-10 minute followup over the phone during the weeks you do not meet with the researcher to explore data or for an interview (probably Week 2 and Week 4 of the course)

The benefits of participating in the study include 3 hours of individualized attention while interacting with data using statistical measures (which can be thought of as individualized tutoring sessions), and an increased exposure to the concepts you are learning in the course. You will also be able to track elements of your life or daily activities that are of interest to you. There will also be monetary compensation for participating, which will be $100 ($20 for each of the two interviews, and $20 for each data exploration meeting).

To participate in the study, you must agree to participate in the above activities, be an undergraduate university student, be 18-28 years old, and be enrolled in Statistics 3000 for the duration of the course.

If you would like you participate in the study, please complete the following form.

Please enter your name below:


Please enter your A# below:


Are you interested in participating in this study?

- Yes
- No
This list contains possible activities and attributes that you could track during your participation in this study. For example, for "Steps," we would provide you with a Fitbit to wear that tracks the number of steps you take in a given day. For "Phone Usage," we would instruct you to download an app to your mobile device that measures and reports how much time you spend on your phone each day. Etc. All of this data will be kept strictly confidential, and is intended solely for your use in learning statistical concepts and practices.

Please place the following list in the order in which they interest you. For example, if Heart rate and Mood are the most interesting to you, they would be at the top of the list, and if Phone Usage and Blood Pressure are the least interesting to you, they would be at the bottom of the list. Thanks.

- Steps
- Sleep
- Heart rate
- Breathing
- Sleep
- Blood Pressure
- Stair Flights
- Mood
- Phone Usage
- Computer Usage

- Air Quality in Home

When are you available to meet for an initial interview? This interview will last no longer than 1 hour. I will send an email to set up a specific time to meet, and this will help me in doing so.

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Provide any relevant comments to further explain or clarify your schedule.

Thank you for your participation! I will contact you shortly to arrange a time to meet. Feel free to contact me at jeffrey.thayne@gmail.com, or Dr. Victor Lee at victor.lee@usu.edu if you have any further questions about the study and your participation.
Appendix C: QSIA (Paper form)

Here is the QSIA in paper form, which was used when recruiting learners in the in-person section of the course during the first few days of the semester:

**Self-data and Statistics Learning Study**

Many students and non-students alike track elements of their daily lives. Some people, for example, wear fitness trackers and pedometers to measure their daily physical activities. Others track how much time they spend on their phone, or their computer. Some track their daily mood swings, or their weight. All of these are part of a growing Quantified Self movement, and yield large amounts of valuable, personally relevant data to users. We think that this data can be leveraged in statistics learning.

To participate in this study, you will be invited to:

- Track two elements of your daily life or activities, found in the list below. We will provide you with the tools that you need to do so.
- Meet with the researcher on 3 separate occasions to explore the data you collect using the statistical concepts and practices you are learning in the course. These meetings will take place around Week 3, Week 5, and Week 6 of the course.
- Participate in two interviews, one right before the course starts (or during the first week of the course), and the second during the last week of the course (or right after it ends). You will also participate in a brief, 10-15 minute followup over the phone during the weeks you do not meet with the researcher to explore data or for an interview (probably Week 2 and Week 4 of the course)
The benefits of participating in the study include 3 hours of individualized attention while interacting with data using statistical measures (which can be thought of as individualized tutoring sessions), and an increased exposure to the concepts you are learning in the course. You will also be able to track elements of your life or daily activities that are of interest to you. There will also be monetary compensation for participating, which will be $100 ($20 for each of the two interviews, and $20 for each data exploration meeting).

To participate in the study, you must be an undergraduate university student, be 18-28 years old, and be enrolled in a university statistics course. If you would like you participate in the study, please complete the form on the other side of this page. If you are selected for the study, we will contact you shortly.

(Reverse Side)

Name: __________________________  A#: _________________________
Age: ________  Email Address: ____________________________

This list contains possible activities and attributes that you could track during your participation in this study. We will lend you whatever tools you need to track the following activities or attributes. For example, for "Steps," we would provide you with a Fitbit to wear that tracks the number of steps you take in a given day. For "Phone Usage," we would instruct you to download an app to your mobile device that measures and reports how much time you spend on your phone each day. Etc. All of this data will be kept strictly confidential, and is intended solely for your use in learning statistical concepts and practices.
On a scale of 1 to 5, please rate the extent to which each of the following interest you. For example, if Heartrate and Mood are very interesting to you, rate them close to 5, and if Phone Usage and Blood Pressure are the least interesting to you, rate them close to 1.

Steps 1 2 3 4 5
Sleep 1 2 3 4 5
Heartrate 1 2 3 4 5
Breathing 1 2 3 4 5
Blood Pressure 1 2 3 4 5
Sleep 1 2 3 4 5
Stair Flights 1 2 3 4 5
Mood 1 2 3 4 5
Phone Usage 1 2 3 4 5
Computer Usage 1 2 3 4 5
Other: ____________ 1 2 3 4 5

When are you available to meet for an initial interview? This interview will last approximately 1 hour. If you are selected to participate in the study, I will send an email to arrange a more specific time to meet. This, however, will help me to narrow down when you are available, and make this process easier. **If you are not available this week, but are available the next week, let me know in the space available below.**

8am 9am 10am 11am 12pm 1pm 2pm 3pm 4pm 5pm 6pm 7pm
TUES
WED
THUR
FRI
Comments:
Thank you for your participation! If you are selected to participate in this study, I will contact you shortly to arrange a time to meet. Feel free to contact me at jeffrey.thayne@gmail.com, or Dr. Victor Lee at victor.lee@usu.edu if you have any further questions about the study and your participation.
Appendix D: Initial Interview Protocol Draft

To begin, I would like to make sure that you know that my purpose is not to evaluate you, your performance in the course, or your participation in the study — nothing you say here can invalidate your participation, or make your participation in the study less valuable to us. I’m not interested in you giving us the right answers — simply the true ones. Our purpose here is not to evaluate, but to simply understand.

Background Questions

• First of all, tell me about what you are studying in school.
  o How did you choose this academic path?
  o What interests you about ____?
  o What do you plan to do with your degree? What do you want to do professionally?
  o Tell me about how might your future look different if you didn’t finish your degree.
  o What would you consider to be your primary reasons for being in school?

• Tell me about why you are taking this statistics course.
  o Where does this class fit in your major?
  o How does taking this course help you?
  o How do you think what you will learn in this course might be helpful to you later on?
o Will what you are learning in this class help you in your future profession? Or future courses? Or your personal life?

o If you were to fail this course, how might your future look different?

o If you were to get an A in this course, but not learn any of the material, how might the future look different? [Or, if you master this course, but then forget everything afterwards?]

o What do you imagine to be the worst thing that could happen if you do not learn the material in this course?

o What do you imagine to be the best thing that could happen if you successfully learn the material in this course?

• Have you ever taken a statistics course before?
  o Tell me about what you learned in that course.
  o Tell me about how what you learned has been useful to you since then.

• How did you decide to participate in this study?
  o What would you consider your primary reasons for being here?
  o In what ways do you think this study might help you?

**Past Experiences with Data**

• Have you ever kept track of anything about yourself?
  o [As needed, provide personal examples (Fitbit, finances, baby’s weight, etc.)]
  o Tell me more about this. What did you keep track of, and why?
Tell me about what you did with the information. That is, how did you analyze it (if you did)?

What did you learn about yourself in the process?

Did you ever use the information when making a decision?

What other things have you kept track of about yourself?

- Have you ever collected data for some other purpose?
  - [As needed, provide personal examples — for example, I’ve collected data for several class projects, analyzed the results using statistics, and presented the results in a conference paper. I’ve also worked on data collection for a few projects for professors.]
  - What was it for?
  - What did you do with the data?

- What other times have you collected data? Why? What did you do, and what did you learn?

- Have you ever calculated an average before, or used an average to make a decision?

- Have you ever used any other statistics concepts before (such as a correlation, a t-test, or anything else)?
  - Have you ever used these statistical concepts outside of class? What for?
    - What did you learn?
• Have you ever had a particularly bad experience when collecting data, using or learning statistics, or anything similar? Have you ever had a particularly good experience [e.g.]?
  o Have your perspective on data, data collecting, or statistics ever changed in any way? If so, how and why?

Quantified Self Choices

• When registering for the study, you mentioned that you might be very interested in tracking your ______.
  o Why are you interested in tracking your ______?
  o Why is this more interesting to you than the other options?
  o What do you imagine learning about yourself by tracking _____?
  o What do you imagine that you could do with the data that you collect?
  o What questions do you have about your _____?
  o How do you think that statistics might help you to answer those questions?

• You also mentioned that you might be very interested in tracking your ______.
  o Why are you interested in tracking your ______?
  o Why is this more interesting to you than the other options?
  o What do you imagine learning about yourself by tracking _____?
  o What do you imagine that you could do with the data that you collect?
  o What questions do you have about your _____?
  o How do you think that statistics might help you to answer those questions?
  o How does _____ relate to your first choice?
• You said that you weren’t at all interested in tracking your ______ and ______.
  o Why are _____ less interesting to you than _____ or _____?
  o What, if anything, would make _____ more interesting to you?
  o What could you learn about yourself if you were to track ______?
Appendix E: Data Exploration Meeting 1 Protocol

Prior to the session, I obtained the data collected by the participant thus far in the study, and ensured that it was formatted in a way that is readable using R. At the beginning of the session, I discussed with the participant their experience collecting the data about themselves:

- How consistent were they in collecting the data? If they were not consistent, why not?
- Did collecting the data lead to any changes in their activities? If so, what changed, and why?
- Have they looked at the data they’ve collected already? If so, what have they discovered so far?
- What do they expect the data to show? Why? What do they expect the daily mean and median to be? What do they expect the hourly mean and median to be?
- What would they be interested in knowing about their data?

We discussed these questions about data sets they have collected. Then, the participant used R — with my help and guidance as needed — to create summary statistics of their data. This included what the means and medians are for each day (or hour, if available), as well as the standard deviations, etc. The participant was then asked to interpret the data:

- What is the highest value? What is the lowest value?
- What is the standard deviation, and what does that tell you?
• What is the daily mean, and the hourly mean? What do these tell you?
• What is the daily median, and the hourly median? How are these similar to or different from the mean? Why might that be?
• Where are the greatest deviations in the data, and what accounts for those deviations?
• Are there outliers in the data? What accounts for those outliers?

These questions were added to and adjusted in the moment based on the specific data that the participants are looking at. I added to and adjusted these questions to complement the kinds of questions found on the participant’s homework and questions asked during class discussions. I also adjusted and added to these questions depending upon the flow of the conversation, the expressed interests of the participants, and the questions they are asking about the data.

For students in the in-person section of Statistics 3000, I also included an exercise in R in which we demonstrated the Central Limit Theorem using their data — we displayed the sampling distribution of the mean with varying sample sizes, and showed how the sampling distribution of the mean began to resemble a normal curve as the sample size increased. The purpose of this exercise was to help them to see that their own data followed the norms and patterns observed by statisticians, and discussed in their class.

After exploring and discussing the summary data of each of their data sets, I moved on to discuss the kinds of questions that are raised by the data:
• Can we learn anything from this summary data about your physical activities or daily life?
• How might these two data sets be related?
• What factors might affect the data in each of these data sets? How could you find out?
• What would you like to learn more about these activities (or aspects of life)?

What further questions do you have? How might you go about answering those questions?

I encouraged the participants to continue to think of interesting questions they could ask about their data, and how they might go about answering them. In addition, we discussed what kinds of questions we might ask and answer in the following data exploration meetings, and whether additional data will need to be collected to answer these questions. I then asked them about their experiences in the course so far:

• What have you learned in the past week of the course? Briefly describe for me what you remember.
• Are these ideas useful to you in the future? Is it personally important to you to master these particular concepts? If so, why?
• Have these things been helpful to you when thinking about your own physical activity data? Why or why not?
Appendix F: Data Exploration Meeting 2 (R)

The purpose of this worksheet was to provide a bit of structure to the data exploration meeting, and to scaffold the learner’s analyses. The assumption was that the learners had just recently learned to perform these analyses, and would need some structured guidance as they performed the analyses on their own data. This was particularly the case for those learners who were using R. For those participants who were using Excel, the same template was followed, except that Excel functions were used instead of R functions. For each participant, we engaged in 2-3 of the following analyses, and discussed the results of those analyses, in similar fashion to the questions included in Appendix E.

The worksheet included different questions for different participants, depending on the forms of self-data they were tracking. These questions included:

Do you use the computer more on weekends than on weekdays?

Do you use the computer for entertainment less per hour during nighttime hours than the total average?

Do you sleep more on the weekends than on the weekdays?

Do you take more steps on sunny days than on rainy days?

Is your heart rate less during nighttime hours than your overall average heart rate for the past 5 weeks?

Do you take fewer steps/hour during nighttime hours than the total average?

Do you use the phone more on weekends than on weekdays?
Do you use the computer more for entertainment on weekends than on weekdays?

Worksheet

**Do you use the computer more on weekends than on weekdays?**

(1) What is the population, and what is the sample?

(2) Is the sample a *random* sample? [Hint: We’re going to have to pretend it is]

(3) What is the parameter of interest?

(4) What would be the null hypothesis?

Using the test statistic, let’s test the null hypothesis.

\[ t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s^2_1}{N_1} + \frac{s^2_2}{N_2}}} \]

(a) First, let’s grab our sample and assign it to the variable “Weekend_Sample.” Use this code to do it:

```r
Weekend_Sample <- Computer_Usage_by_Day $Sum_Distracting[wday(Computer_Usage_by_Day$Day) == "1" | wday(Computer_Usage_by_Day$Day) == "7"]
```

This code takes the “Sum_Distracting” column of our “Computer_Usage_by_Day” data frame, and stores it in Weekend_Sample — but *only* those rows where the weekday value of the “Day” column equals “1” or “7.” The <- symbol is what you use to “assign” things to a variable, in this case Weekend_Sample.

(b) Then, let’s find the mean of our Weekend_Sample. We can do that using the mean() function, with “Weekend_Sample” as its argument. Let’s assign the mean to a new variable, Weekend_Mean. Here’s the code for that:
Weekend_Mean <- mean(Weekend_Sample)

(c) Now, let’s find the standard deviation of our weekend sample, and assign it to a variable, Weekend_SD. You can find the standard deviation using the function sd(). Based on the previous instructions, see if you can figure out how to do that.

(d) Now, let’s create a variable that stores the “N” of our weekend sample, and call it Weekend_N. You can find the number of values in a vector using the function length(). Hint: you’ll do the same thing as you did in the last two, but with length() instead.

(e) Now, we’ll do the same thing for our Weekday_Sample. To get the weekday sample, use the following code:

```r
Weekday_Sample <- Computer_Usage_by_Day
$Sum_Distracting[wday(Computer_Usage_by_Day$Day) != "1" & wday(Computer_Usage_by_Day$Day) != "7"]
```

This does the reverse of the other one — it takes the “Sum_Distracting” column of our “Computer_Usage_by_Day” data frame, and stores it in Weekend_Sample — but only those rows where the weekday value of the “Day” column does NOT equal “1” or “7.”

(f) Now create 3 new variables: Weekday_Mean, Weekday_SD, and Weekday_N, using the same techniques as before. Let’s write all the results down. You can display each variable by simply typing its name and pressing enter.

Weekend_Mean: Weekday_Mean:
Weekend_SD: Weekday_SD:
Weekend_N: Weekday_N:

(5) So, what are your predictions? Do you think the null hypothesis is true or false, based on these numbers?
The test statistic will help us see how likely the difference between our means is due to chance (because of the random sample we drew), were the null hypothesis true. So let’s run the test statistics. It’s a complicated line of code. Jeff has it already written into the computer to save time writing it out. But if you look closely, you can see it’s just using the values you computed to compute the test statistic:

\[
t_{test} = \frac{Weekend\_Mean - Weekday\_Mean}{\sqrt{\frac{Weekend\_SD^2}{Weekend\_N} + \frac{Weekday\_SD^2}{Weekday\_N}}}
\]

We’ll also need to compute the degrees of freedom, an even more complicated piece of code:

\[
Degrees\_Freedom = \frac{\left(\frac{Weekday\_SD^2}{Weekday\_N} + \frac{Weekend\_SD^2}{Weekend\_N}\right)^2}{\left(\frac{Weekday\_SD^2}{Weekday\_N}\right)^2/(Weekday\_N-1) + \left(\frac{Weekend\_SD^2}{Weekend\_N}\right)^2/(Weekend\_N-1)}
\]

Let’s write the results down:

\[
t_{test}: \quad degrees\_freedom:
\]

Let’s look at a p-table to see how likely this result is (if the null hypothesis is true).

Probability:

(6) So what conclusions should we draw from these results? Could we reject the null hypothesis?
Appendix G: Final Interview Protocol Draft (Sarah)

Introduction

Thanks again for your participation in this study. I would like to understand your experience with this study. Every participant’s experiences have been different. My purpose here is not to evaluate you, your performance in the course, or your participation in the study — nothing you say here can make your participation in the study less valuable to us. We are not looking for any particular answer. In fact, we do not expect that self-data of this sort will matter for all students, or that using it in statistics will be equally rewarding or helpful for every student.

Narrative experiences

I’m wondering if, to start with, you can tell me the story of your participation with this study, from beginning to end. I know that I’ve been here all along, but I would like to hear from your side of the story.

Motivations for participating in study

When asked before, you said that one reason for participating in the study was because it would be really cool to participate and see how it works. You also said that it would be interesting to track your sleep and things. Did your reasons for participating in the study change at all during the past month and a half since we first met? If so, in what way and why?

Quantified Self
Let’s revisit the list we had at the first meeting. You mentioned that you were particularly interested in tracking your sleep, your mood, and your steps. After tracking your sleep for 3 months for this study, was it as interesting to you as you imagined going in? Was tracking your mood as interesting to you as you imagined? Why or why not? What about your steps? What would have made these more interesting to you?

What kinds of questions would you want to ask about your sleep or mood that we didn't get to ask in the study? Do you think that you'll take the time to try and answer these questions?

You marked breathing and blood pressure as less interesting to you, and less relevant to your life. Would you still consider this to be the case?

If you could choose again any two elements from this list to track, what would you choose? Would it be the same or different than before? Why?

If you had a Fitbit of your own like the one you've been using, do you think you'd continue tracking your steps, sleep, or mood? If so, why? Do you think that you'll continue to use statistics to look at the data, like we’ve done? How so? What questions would you ask? If I were to show you how to continue collecting and exploring your own data during future statistics courses, like we have during this one, would you do so? Why or why not? Would you do so even if there were no compensation for participating? Why or why not?

What other elements of your life, environment, or activities would you be interested in tracking and learning about? What questions would you ask? How would you go about finding the answers?
Data Exploration Meetings

How else has your behavior changed as a result of your tracking? Have tracking these elements of your life maintained your interest over time? How so? Why or why not?

So we looked at hypothesis testing the third time we met. Have you used hypothesis testing in your work? Can you imagine a situation in which you could use hypothesis testing?

At the time, we asked whether you walk more on weekends than on weekdays. How important was the answer to this question to you? In the analysis, we failed to reject the null hypothesis, which means that we didn’t have enough evidence to conclude that the true means are different. How significant is that to you? What questions would you want to ask further or instead?

We also asked whether you sleep more on weekends than on weekdays. How important was the answer to this question to you? In the analysis, we failed to reject the null hypothesis. How significant is that to you? What questions would you want to ask further or instead?

We also asked whether your mood is different on weekends than on weekdays. How important was the answer to this question to you? In the analysis, we rejected the null hypothesis. How significant is that to you? What questions would you want to ask further or instead?
You mentioned at the time that you got to use what you have learned for the first time – were there opportunities for application in the course?

We looked at correlation the last time we met. Have you used correlation in your work? Can you imagine a situation in which you could use correlation?

At the time, we asked whether your sleep depended on how much you walk during the day. How important was the answer to this question to you? In the analysis, we found a small, negative correlation between sleeps and steps. How significant is that to you? What questions would you want to ask further or instead?

We also asked whether your mood depends on how much you walk. How important was the answer to this question to you? In the analysis, didn’t find any correlation. How significant is that to you? What questions would you want to ask further or instead?

We also asked whether your mood depends on how much you sleep. How important was the answer to this question to you? In the analysis, did found a correlation between happiness and sleep – a negative correlation. How significant is that to you? What questions would you want to ask further or instead?

Finally, we asked whether how relaxed you are is correlated with restless time. In the analysis, we found a negative correlation (more relaxed = less restless time). How significant is that to you? What questions would you want to ask further or instead?

**Experience with statistics course**

Tell me about your experiences with the statistics course. You said before that the course is required for your major. Knowing what you know now, if it wasn’t required for your
major, would you have still taken it? Why or why not? How did the course match up to your expectations? What was the most surprising thing about the course?

You said before that you don’t like statistics as much because it was more application based, and you like the more abstract part of math better. Has this changed while you’ve been taking the course? If so, how, and why?

How have your experiences in the couple months in this course and this study influence how you think about statistics, and data? What have you learned that you think will help you in your work as a math teacher?

How has learning statistics affected your life so far, in other ways than we’ve touched on? How else has your perspective on data, data collecting, or statistics changed or evolved in the past 2 months? If so, how and why?

Is statistics something that you see as important to your future students? Why or why not?

Has the way the material matters to you changed over the past month and a half? If so, how and what do you feel has contributed most to that?

Looking back on the course now, what do you think is the most helpful thing that you’ve learned? Why? Conversely, what do you think is the least helpful thing that you’ve learned? Why?

When you did you homework or your projects, what data did you work with? Where did the data come from? How interesting what the data to you? Tell me about the projects you did in the course. What questions did you ask? How much did the answers to those questions matter to you?
Improving the Experience

What did you think about the data collection? Some people enjoyed it, and others found it annoying. What about you?

Do you feel that exploring your own data enhanced your learning experience in the course, even though it was not an official part of the course? If so, how? Did collecting and exploring self-data help you in any of your assignments for the statistics course? If so, how, and why?

What could have made self-data explorations more meaningful to you?

If you could make any suggestion for improving the self-data exploration experiences in this study, what would it be? How could future students explore their own data using statistics better than we have done here?

Imagine that this self-data was part of a class, instead of personal meetings with me — what do you think that would have been like? Would your experience have been the same, or different? Would you like to see self-data used as a regular part of statistics courses? Why or why not?

Would you recommend this study to other statistics students? Why or why not?
CURRICULUM VITAE

JEFFREY L. THAYNE
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EDUCATION
Ph.D. (2016) Instructional Technology and Learning Sciences
Utah State University, Logan, Utah
Advisor: Victor Lee

M.S. (2012) Psychology
Specialization: Theoretical Psychology
Brigham Young University, Provo, Utah
Advisor: Dr. Edwin Gantt

B.S. (2009) Psychology
Brigham Young University, Provo, Utah
Honors: Cum Laude Graduate and University Honors

RESEARCH INTERESTS

Theoretical issues related to learner motivation and engagement; practical application of motivation theory in instructional design and teaching; the role of agency and moral responsiveness in learning theory; the institutional, structural, and social factors that influence long-term student motivation and engagement.

PUBLICATIONS and PRESENTATIONS


in existential and positive psychology (pp. 185-204). London, UK: Springer Publications.


Theses and Reports:


COURSES TAUGHT and DESIGNED


2013-2014  Instructor: ITLS 5105/6105 — Distance Learning Tools, Utah State University

2014  Creator: Psych 353 — LDS Perspectives and Psychology, Brigham Young University. I co-authored this online course for BYU Independent Study with Dr. Edwin Gantt.

2012  Instructor: Psych 111 — General Psychology, Brigham Young University. An introductory course for incoming undergraduates.

2012  Instructor: Psych 341 — Personality Theory, Brigham Young University.

2010-2011  Instructor: Educational Psychology, Brigham Young University.

2010  Teaching assistant: Psych 210 — History of Psychology, Brigham Young University.

2008-2009  Teaching assistant: Psych 353 — LDS Perspectives in Psychology, Brigham Young University.

2008  Teaching assistant: Psych 302 — Psychological Statistics, Brigham Young University.

RESEARCH EXPERIENCE

2014-2015  Research Assistant to Dr. Victor Lee, Instructional Technology and Learning Sciences, Utah State University. I engaged in in-classroom on the field-work in a nearby elementary school, implementing a carefully designed statistics module leveraging data collected by learners using Fitbit activity trackers. Additionally, I participated in a qualitative analysis of the video data, quantitative analysis of pre-post test scores, and subsequent writing for conference presentations and journal submissions.

2013-2015  Research Assistant to Dr. Yanghee Kim, Instructional Technology and Learning Sciences, Utah State University. I performed quantitative analyses, literature review, and paper writing for two existing research projects related to learner engagement, anxiety, and learner-instructor relationship building in mathematics instruction.
2013  **Research Assistant** to Dr. Brian Belland, Instructional Technology and Learning Sciences, Utah State University. I performed coding on qualitative data on a project that implemented a problem-based learning science curriculum in a nearby elementary school, and helped write about the analysis.

2011  **Research Assistant** to Dr. Noel Reynolds, Political Science, Brigham Young University. I engaged in extensive reviews of existing literature related to the philosophy of law, and help construct arguments and theories about the origins of legal obligation.

2008  **Research Assistant** to Dr. Gerrit Gong, Academic Vice President of Brigham Young University. I assisted in literature research related to his work in the administration.

**AWARDS and HONORS**

Presidential Doctoral Research Fellowship, Utah State University (2012-2016)
Institute for Humane Studies Fellowship, Institute for Humane Studies (2010-2015)
Renshaw Fellowship, Intercollegiate Studies Institute (2013)
Heritage Scholar, Brigham Young University (2003-2009)

**PROFESSIONAL MEMBERSHIPS**

2015-2016  *Association for Educational Communications and Technology*

**TECHNICAL SKILLS**

R programming, SPSS, and data analysis
HTML, CSS, PHP, and Javascript
Photoshop, Illustrator, InDesign, QuarkXPress
Adobe Captivate, Camtasia, AfterEffects, iMovie