Engaging in Data Practices in Summer STEM Programs: A Person-in-Context Approach

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Chapter 1

Introduction

Changes in how we plan our day-to-day lives, communicate, and learn are increasingly impacted by data. These sources of data–quantitative and qualitative–are created by us, for us, and about us, although at present opportunities for learners to analyze data in educational settings remain limited. Work with data more broadly includes processes of collecting, creating, modeling data, and asking questions that may be answered with data and making sense of findings.

Work with data, then, is more than just crunching numbers or interpreting a figure created by someone else, but rather is about making sense of phenomena and problem solving, a point particularly relevant to work with data in educational contexts (Lee & Wilkerson, 2018; Wild & Pfannkuch, 1999). Aspects of work with data cut across STEM domains and are recognized as core competencies in both the Next Generation Science Standards and the Common Core State Standards (National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010; NGSS Lead States, 2013). Scholars have pointed out the benefits of analyzing data for learners as young as two years old (Gopnik, & Sobel, 2000).

In supporting teachers and learners' data analysis efforts, some scholars have focused on key data analytic processes, particularly those related to generating measures of phenomena and creating data models, using these as anchoring practices for other aspects of work with data, like posing questions (English, 2012; Lehrer & Romberg, 1996; Lesh, Middleton, Caylor, & Gupta, 2008). Findings from this area of research suggest that engaging in these practices "has an exceptionally high payoff in terms of students' scientific reasoning" (Lehrer & Schauble, 2015, p. 696) and can highlight the utility of mathematics for students' lives (Lesh, Middleton, Caylor, & Gupta, 2008).

Learners' experiences, considered from the perspective of engagement theory, consist not only of cognitive processes, but also behavioral and even affective dimensions, too (Fredricks, Blumenfeld, & Paris, 2004; Skinner & Pitzer, 2012). When learners' experiences are considered in terms of their engagement, we can hypothesize that learners who are engaged in high-quality activities related to work with data will be more or less cognitively, behaviorally, and affectively engaged. This engagement is a key outcome in its own right and may be an antecedent of changes in other outcomes, such as students' intention to pursue an area of study or career in a STEM domain.

While scholars have looked at cognitive outcomes and learners' capability to participate in specific, learners' experiences of working with data has not been the focus of past research. Thus, the present study sets out to understand to how learners' experiences are impacted by work with data. In this study, I use contemporary engagement theory as a framework to understand learners' experience. In this framework, engagement is considered to multi-dimensional and dynamic, or changing over time (Fredricks & McColskey, 2012). Scholars commonly consider engagement in terms of three dimensions: cognitive (i.e., use of meta-cognitive learning strategies), behavioral (hard work on a task), and affective dimensions (enjoyment; Fredricks, Blumenfeld, & Paris, 2004; Sinatra, Heddy, & Lombardi, 2015; Skinner & Pitzer, 2012). In recognition of its dynamic nature, some engagement scholars have usefully drawn upon flow theory (Csikszentmihalyi, 1990, 1997) to identify not only dimensions of engagement, but also other, subjective, characteristics that effect engagement.

This past research, drawn upon in the present study, has considered how learners' perceived competence and challenge act as key conditions of engagement (Shernoff, Kelly, Tonks, Anderson, Cavanagh, Sinha, & Abdi, 2016), aligning with situated views of learning (Sfard, 1998) and motivation (Nolen, Horn, & Ward, 2015).

The purpose of this study, then, is to understand learners' experience of engaging in work with data.. Engagement is understood in terms of cognitive, behavioral, and affective dimensions, and the conditions that support engagement are understood in terms of two subjective components that past research and theory suggest influence engagement: perceived challenge and perceived competence. Work with data is considered in terms of specific aspects, such as asking questions and generating and modeling data, identified from past research. Engagement in work with data is explored in the context of outside-of-school STEM enrichment programs carried out during the summer.

Chapter 2

Literature Review

I define work with data as a key practice across STEM domains. I also present a multi-dimensional approach to understanding engagement that considers engagement and the two influencers of engagement (perceptions of competence and challenge) in order to establish the conceptual framework used in the present study.

2.1 Defining Work With Data

Scholars have conceived of working with data in different ways, but some core components have emerged. Some scholars have focused on a few key pieces of data analysis connected through the use of "data to solve real problems and to answer authentic questions" (Hancock et al., 1992, p. 337). This approach is commonly described as including two goals:

1. Creating data through constructing measures and collecting data
2. Accounting for variability in data through models, or data modeling (English, 2012; Hancock et al., 1992; Lehrer & Romberg, 1996; Lesh et al., 2008)

This approach has primarily been taken up by mathematics educators and is reflected in statistics curriculum documents (Franklin et al., 2007). In science settings, where answering questions about phenomena serve as the focus of activities, it shares features of the process of engaging in scientific and engineering practices but has been less often studied.

Wild and Pfannkuch (1999) consider the process in terms of identifying a problem, generating a measurement system and sampling plan, collecting and cleaning the data, exploring the data and carrying out planned analyses, and interpreting the findings from the analysis. Such a process is common in STEM content areas, particularly across statistics education research and is instantiated in standards for curricula: Franklin et al.'s guidelines for the American Statistical Association focus on the Framework for statistical problem solving: formulating questions, collecting data, analyzing data, and interpreting results (2007). The goals of this framework and its components are similar to Hancock et al.'s (1992) description of "using data to solve real problems and to answer authentic questions" (p. 337). Scholars have subsequently expanded Hancock et al.'s definition of to include six components: asking questions, generating measures, collecting data, structuring data, visualizing data, and making inferences in light of variability (see Lehrer & Schauble, 2004). The last of these components is crucial across all of the visions of work with data reviewed here and distinguishes these processes from other aspects of data analysis: Accounting for variability (or uncertainty) is central to solving real-world problems with data and the process of data modeling.

In the present studies, these different approaches to working with data are distilled into five key aspects (see Figure 1) that guide the conceptualization of this study:

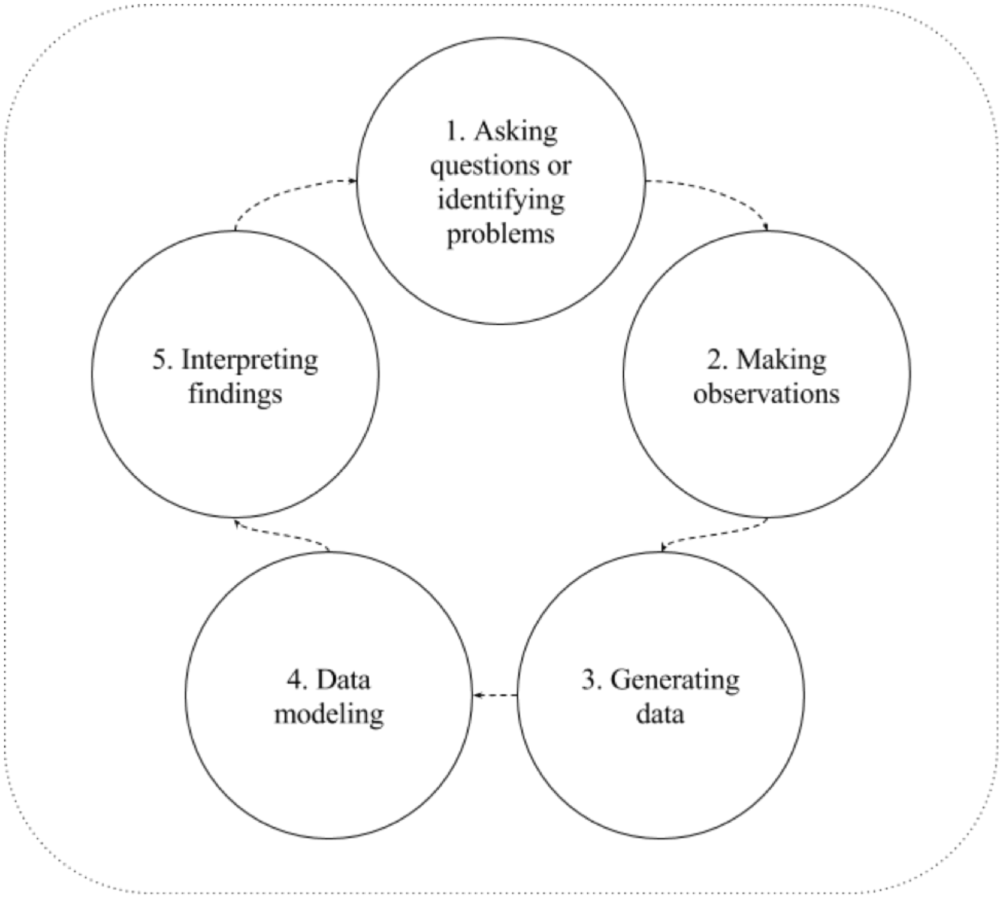

Figure 2.1: Work with data in STEM education settings

- Asking questions: Generating questions that can be answered with empirical evidence
- Making observations: Watching phenomena and noticing what is happening with respect to the phenomena or problem being investigated
- Generating data: The process of figuring out how or why to inscribe an observation as data about a phenomena, as well as generating coding frames or tools for measuring
- Data modeling: Includes simple statistics, such as the mean and variance, as well as more complicated models, such as linear models and extensions of the linear model
- Interpreting and communicating findings: Activities related to identifying a driving question regarding the phenomena that the question is about

The five practices are a cycle because not only does each part follow that before it, but also because the overall process is iterative: interpreting findings commonly leads to new questions and subsequent engagement in work with data.

Also, as depicted in Figure 1, scholars have pointed out some key features of how work with data is carried out that impact their effectiveness as a pedagogical approach. These key features include an emphasis on making sense of real-world phenomena and iterative cycles of engaging in work with data and collaboration and dialogue, through which ideas and intermediate findings are critiqued and subject to critique, and revised over time (McNeill & Berland, 2017). As I will discuss later, these factors might have the potential to impact engagement through the proximal conditions of challenge and competence.

2.2 The role of work with data in the curriculum

Scholars argue that work with data can serve as an organizing set of practices for engaging in inquiry in STEM settings (Lehrer & Schauble, 2015). Data are both encountered and generated by learners, and so opportunities for STEM students to work with data provide many opportunities to leverage students' curiosity because processes of inquiry can be grounded in phenomena that learners themselves can see and manipulate or phenomena that learners are interested in. Also important, becoming proficient in work with data can provide learners with an in-demand capability in society, owing to the number of occupations, from education to entrepreneurship, that demand or involve taking action based on data (Wilkerson & Fenwick, 2017). Furthermore, becoming proficient in work with data can be personally empowering because of the parts of our lives—from paying energy bills to interpreting news articles—that use data.

Recent reform efforts emphasize work with data (i.e., the scientific and engineering practices in the NGSS and the standards for mathematical practice in the Common Core State Standards). However, work with data is uncommon in many classroom settings (McNeill & Berland, 2017), and so learning environments suited to engaging in work with data, but not explicitly designed to support it, may be valuable to study because they may serve as incubators of these rare and challenging learning activities.

Work with data is related to what is commonly described as data analysis in K-12 settings, though data analysis as described in curricular standards and policy documents can take many forms: from learning about what is already known to systematic efforts to measure large, small, or hard to study phenomena. Data analysis includes both individual cognitive processes, such as reasoning about what counts as a good source of data and coordinated social processes, like sharing what is found with others (Lovett & Shah, 2007). Many policy and curricular documents characterize data analysis as using data to explain or predict phenomena (i.e., National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010; NGSS Lead States, 2013). The range of capabilities included within data analysis is large, ranging from collecting insufficient data to construct an answer to a question, interpreting already-created figures or analyzing already-collected data, and seeking to develop answers to questions that are already known. In addition, teachers and other stakeholders do data analysis in very different ways, with greater or lesser veracity to the aims of data analysis (McNeill & Berland, 2017). Thus, work with data as defined in this study include both more specific aspects of data analysis (constructing measures and data modeling) and more general aspects, such as asking questions and interpreting findings.

Outside-of-school programs are a potentially valuable setting to explore engagement in work with data because of the combined pedagogical and technical expertise of their staff and the activities learners do during their participation in them. Staff for these programs includes educators and scientists, engineers, and others with the technical experience. Additionally, the programs were designed to involve learners in the types of real-world practices experienced by experts in STEM disciplines. Attendance in such programs is associated with many benefits to learners (Green, Lee, Constance, & Hynes, 2013; see Lauer, Akiba, Wilkerson, Apthorp, Snow, & Martin-Glenn, 2006, for a comprehensive review). These programs are also selected because little research has examined how data are part of the experiences of youth in out-of-school-time programs, despite its place as one of a few core practices in STEM. While these reasons to study work with data focus on outside-of-school programs, they are also germane to more formal learning environments, such as classrooms, in which teachers want to design opportunities for their learners to work with data. This is important even for those teachers who themselves have technical expertise, but who have experienced limited training and support for engaging learners in work with data. Therefore, these programs can provide insight into whether engaging in work with data is associated with more optimal forms of engagement in the conditions like those for classrooms in which engaging in work with data is a novel and potentially promising approach to doing and learning about STEM.

2.3 What We Know (And Do Not Know) About How Youth Work with Data

Research related to work with data has been carried out by developmental and educational psychologists as well as by mathematics and science educators (see Lehrer and Schauble, 2015, for a review). This research has been carried out in laboratories and classroom settings. For this study, key findings from past studies are organized around three themes:

1. Specific cognitive outcomes
2. Learners' capability to participate in each of the aspects of work with data
3. Strategies to address key challenges of engaging in each of the aspects of work with data

First, scholars have researched cognitive capabilities related to work with data. Much of this laboratory-based research has focused on how children develop the capability to inductively reason from observations (Gelman & Markman, 1987). Other research has focused on the development of causal, or mechanistic, reasoning, among young children (Gopnik et al., 2001; Gopnik & Sobel, 2000), often from a Piagetian, individual-development focused tradition (i.e., Piaget & Inhelder, 1969). A key outcome of engaging in work with data has to do with how learners account for variability (Lehrer, Kim, & Schauble, 2007; Petrosino, Lehrer, & Schauble, 2003; Lesh, Middleton, Caylor, & Gupta, 2008; Lee, Angotti, & Tarr, 2010), arguably the main goal of engaging in work with data (Konold & Pollatsek, 2002). From this research, we know that learners can develop the capacity to reason about variability (and covariability).

Second, we know that different aspects of work with data pose unique opportunities and challenges. Asking empirical questions requires experience and ample time to ask a question that is both able to be answered with data and which is sustaining and worth investigating (Bielik, 2016; Hasson & Yarden, 2012). Constructing measures, such as of the height of the school's flagpole, requires negotiation not only of what to measure, but how and how many times to measure it (Lehrer, Kim, & Schauble, 2007). Regarding modeling, not only teaching students about models, such as that of the mean, but also asking them to create them, are valuable and practical (Lehrer & Schauble, 2004; Lehrer, Kim, & Jones, 2011), but also time-intensive. Interpreting findings, especially in light of variability through models, and communicating answers to questions, means not only identifying error but understanding its sources, and can be supported through exploring models that deliberately represent the data poorly, but can be instructive for probing the benefits and weaknesses of models (Lee & Hollebrands, 2008; Lehrer, Kim, & Schauble, 2007).

In the context of these opportunities and challenges, how learners participate in different aspects of work with data in terms of engagement theory has not been a focus of research. Consider the process of structuring data, commonly described as a—or the—key part of many applied data analyses, that is also under-emphasized in students' use of data in science settings in which students are provided already-processed, or plotted, data (McNeill & Berland, 2017). How challenging do students perceive these activities to be? How to they perceive their competence regarding this activity? More importantly, how do they engage—cognitively, behaviorally, and affectively—during these experiences? Knowing more about these processes could help us to develop informed recommendations for teachers and designers intending to bring about opportunities for learners to engage in work with data in a better-supported way that is sustained over time.

Third, strategies to support engagement in work with data have included design of curricula, development of instructional strategies supported through collaborations between researchers and teachers, and often, technological tools. At present, opportunities for students to engage in work with data, or analyze data to solve real problems and to answer authentic questions, are limited in K-12 STEM settings. Much of the research in science settings focuses on evidence use, which can include data, but also includes other forms of evidence, such as those from authoritative sources (McNeill & Berland, 2016). Furthermore, creating and constructing models of primary data takes ample time (Dickes, Sengupta, Farris, & Basu, 2016), and doing so even in mathematics settings is uncommon (Lehrer & Schauble, 2015). Furthermore, providing opportunities for students to engage in work with data requires a shift in educational norms and curricular resources, aligned standards and assessments, and teacher professional development (McNeill & Berland, 2017; Wilkerson-Jerde, Andrews, Shaban, Laina, & Gravel, 2016). From this research, we know about specific strategies and learning progressions for learners to develop this capability, such as the role of measurement in exposing learners in a direct way to sources of variability (Petrosino et al., 2003), role of simulation to learn about sampling distributions (Stohl & Tarr, 2002), and use of relevant phenomena, such as manufacturing processes, such as the size of metallic bolts, which can help learners to focus on “tracking a process by looking at its output” (Konold & Pollatsek, 2002, p. 282).

2.4 Engagement in STEM Domains

The nature of engagement is discussed in terms of general features that have been identified across content area domains, conditions that support engagement, and differences between engagement in general and in STEM settings. This is followed by a discussion of two key features of engagement: its dynamic characteristics and what a person-oriented approach to its study can add to research about engagement and its impact on learning and other outcomes.

General characteristics of engagement. Engagement is defined in this study as active involvement, or investment, in activities (Blumenfeld et al., 2004). Explaining how learners are involved in activities and tasks is especially important if we want to know about what aspects of work with data are most engaging (and in what ways), and therefore can serve as exemplary for others advancing work with data as well as those calling for greater support for engagement. Apart from being focused on involvement, engagement is often thought of as a meta-construct, that is, one that is made up of other constructs (Skinner & Pitzer, 2012; Skinner, Kindermann, & Furrer, 2009). By defining engagement as a meta-construct, scholars characterize it in terms of cognitive, behavioral, and affective dimensions that are distinct yet interrelated (Fredricks, 2016). We know from past research that the cognitive, behavioral, and affective dimensions of engagement can be distinguished (Wang & Eccles, 2012; Wang & Holcombe, 2012) and that while there are long-standing concerns about the conceptual breadth of engagement (Fredricks et al., 2016), careful justification and thoughtful use of multidimensional engagement constructs and measures is warranted based on past research.

Recent scholarship has summarized key characteristics of engagement and outcomes from being engaged at school and in other learning environments (Fredricks, 2016), defined for STEM domains in the next section. Engagement is also considered to be dynamic and changing in response to individual, situation or moment, and broader contextual factors, such as the family, classroom, or outside-of-school programs. Many conceptualizations of engagement include cognitive, behavioral, and affective dimensions, but the contents of these dimensions can vary across domains, as discussed in the next section about STEM content areas.

Characteristics of engagement in STEM domains. Engagement in STEM settings shares characteristics with engagement across disciplines, yet there are some distinct aspects of it (Greene, 2015). While one type of engagement—behavioral—is associated with positive outcomes, many STEM practices call for engagement in additional ways (Sinatra et al., 2015), especially around epistemic and agency-related dimensions. For example, many scholars have defined scientific and engineering practices as epistemic practices, which involve applying epistemic considerations around sources of evidence and the nature of explanatory processes (Berland et al., 2016; Stroupe, 2014). The emphasis on developing new knowledge and capabilities through engaging in STEM practices is a potentially important aspect. This is important because measures of engagement might need to be modified for use in STEM domains. Because of the importance of constructing knowledge to engagement in STEM practices, then, cognitive engagement is defined for this study in terms of learning something new or getting better at something.

The behavioral and affective aspects of engagement in STEM settings are arguably more similar to engagement in general than cognitive engagement. While sometimes defined in terms of extra-curricular involvement or following directions, behavioral engagement is defined in this study as working hard at and concentrating on learning-related activities (Fredricks et al., 2004; Singh, Granville, & Dika, 2002). Finally, affective engagement is defined as affective responses to activities, such as being excited, angry, or relaxed (Pekrun & Linnenbrink-Garcia, 2012).

Key conditions that support engagement. In particular for engagement, past research has shown that ESM can help us to find out what conditions support it. Past research suggests that not only learner-level characteristics, such as learners' interest in the domain of study, but also dynamic, changing moment-to-moment conditions are also important (Shernoff et al., 2003; Shernoff et al., 2016; Shumow, Schmidt, & Zaleski, 2013). Focusing on dynamic conditions, Emergent Motivation Theory (EMT; Csikszentmihalyi, 1990), provides a useful lens. From EMT, a key momentary influencer of engagement is how difficult individuals perceive an activity to be, or its perceived challenge. Another key influencer is how good at an activity individuals perceive themselves to be, or their perceived competence. Most important, from the perspective of EMT, being challenged by and good at an activity are especially engaging experienced when together. Past research has supported this contention. Shernoff et al. (2016), for example, demonstrated that while challenge and skill with high levels of one but low levels on the other (i.e., high challenge and low skill) were not broadly associated with positive forms of engagement, their interaction was, suggesting that learners' perceptions of the challenge of the activity, and their perceptions of how skillful they are, are important for explaining why learners engage.

Other key conditions that support engagement concern teacher support (Strati, Schmidt, & Maier, 2017). Particularly concerning work with data, which is demanding not only for learners but also teachers, sustained support from teachers is an essential component of learners being able to work with data (Lehrer & Schauble, 2015; Wilkerson, Andrews, Shaban, Laina, & Gravel, 2016). Consequently, this study considers not only profiles of engagement, but also the conditions of engagement as part in terms of both learners' subjective experiences. The conditions included in the PECs relate to learners' subjective perceptions of two key factors suggested by past research and theory, in particular, how challenging they perceive the activity to be and how good at it they perceive themselves to be (Csikszentmihalyi, 1990). In recognition of differences among learners in their tendency to engage in different (higher or lower) ways in specific activities based in part on individual differences (Hidi & Renninger, 2006), learners' interest in STEM before the start of the programs is also considered as a factor that can impact engagement. Finally, gender and the racial and ethnic group of students is added, as past research has indicated these as factors that influence engagement in STEM (Bystydzienski, Eisenhart, & Bruning; Shernoff & Schmidt, 2008). These conditions are different from those discussed in the section on the five aspects of work with data in that they are teacher-related factors (with respect to instructional support), subjective factors (with respect to perceptions of challenge and competence), and demographic characteristics, whereas a focus on real-world phenomena, iterative cycles, and collaboration and dialogue may potentially impact engagement through learners' perceiving the activity to be supported by the subjective contextual conditions of challenge and competence.

2.5 Using ESM to Study the Dynamics of Engagement

A number of scholars, in recognition of the dynamic nature of engagement, have explored the use of Experience Sampling Method (ESM) to understand engagement (e.g., Strati et al., 2017)—or have recommended it is as a valuable approach for doing so (Turner & Meyer, 2000; Sinatra et al., 2015). ESM involves asking—usually using a digital tool and occasionally a diary—to ask participants short questions about their experiences. ESM is particularly well-suited to understanding the dynamic nature of engagement because students answered brief surveys about their experience when they were signaled, minimally interrupting them from the activity they are engaged in and also seeking to collect measures about learners' experience when signaled (Hektner, et al., 2007).

Research has shown us how the use of ESM can lead to distinct research contributions. Shernoff, Csikszentmihalyi, Schneider, and Shernoff (2003) examined engagement through the use of measures aligned with flow theory, namely, using measures of concentration, interest, and enjoyment (Csikszentmihalyi, 1997). In a study using the same measures of engagement (concentration, interest, and enjoyment) Shernoff et al. (2016) used an observational measure of challenge and control (or environmental complexity) and found that it significantly predicted engagement, as well as self-esteem, intrinsic motivation, and academic intensity. Schneider et al. (2016) and Linnansaari et al. (2015) examined features of optimal learning moments or moments in which students report high levels of interest, skill, and challenge, as well as their antecedents and consequences. Similar to ESM in that through its use engagement can be studied in a more context-sensitive, still other scholars have used daily diary studies to examine engagement as a function of autonomy-supportive classroom practices (Patall, Vasquez, Steingut, Trimble, & Pituch, 2015; Patall, Steingut, Vasquez, Trimble, & Freeman, 2017). This past research that used ESM (or daily diary studies) to study engagement has shown us that the methodological approach can be used to answer questions that were hard to answer using the more-traditional pre- or post-survey measures.

Other research shows us that there are newer approaches to analyzing ESM data that can contribute insights into the dynamics of engagement in a more fine-grained way. For example, Strati et al. (2017) explored the relations between engagement to measures of teacher support, finding associations between instrumental support and engagement and powerfully demonstrating the capacity of ESM to understand some of the dynamics of engagement. Similarly, Poysa et al. (2017) used a similar data analytic approach as Strati et al. (2017), that is, use of crossed effects models for variation within both students and time points, both within and between days. These studies establish the value of the use of ESM to understand the dynamics of engagement and that such an approach may be able to be used to understand engaging in work with data. Additionally, these studies show that how effects at different levels are treated, namely, how variability at these levels is accounted for through random effects as part of mixed effects models, is a key practical consideration for analysts of ESM data.

2.6 A Person-Oriented Approach to Momentary Engagement

One powerful and increasingly widely used way to examine dynamic constructs holistically is a person-oriented approach, which can be used to consider the way in which psychological constructs are experienced together and at once in the experiences of learners. In the context of the present study, this approach can help us to identify naturally occurring profiles of momentary engagement. In the context of the present study, these profiles seek to capture both the cognitive, behavioral, and affective dimensions of engagement and the subjective conditions of challenge and competence to understand how students experience engagement and its conditions in a more holistic way. The person-oriented view, developed within developmental science, emphasizes these groups of constructs in light of the dynamic nature of learning and development, and the importance of both person-level and contextual factors upon these dynamics (Bergman & El-Khouri, 1997; Magnusson & Cairns, 1996), though recent conceptions of the developmental science approach sometimes differ in the extent to which they acknowledge these contextual factors (Witherington, 2015). Though studies examining learning from a person-oriented perspective are not very common, some examples include studies of intrinsic and extrinsic motivation (Corpus & Wormington, 2014; Hayenga & Corpus, 2010), profiles of achievement goals (see Wormington & Linnenbrink-Garcia, advance online publication, for a review), and epistemic cognition (Trevors, Kendeou, Braten, & Braasch, 2017).

There are some recent studies taking a person-oriented approach to the study of engagement (i.e., Salmela-Aro, Moeller, Schneider, Spicer, & Lavonen, 2016a; Salmela-Aro, Muotka, Alho, Hakkarainen, & Lonka, 2016b; Van Rooij, Jansen, & van de Grift, 2017; Schmidt, Rosenberg, & Beymer, advance online publication). Van Rooij et al. (2017) identified five secondary school student profiles, derived from three dimensions of student engagement: behavioral engagement, cognitive engagement, and intellectual engagement. Salmela-Aro et al. (2016b) examined burnout and engagement using a person-oriented approach. While not using ESM, this study demonstrated the use of a person-oriented approach including (although not focused on profiles comprised exclusively of) engagement. Examining the same variables (engagement and the three aspects of school burn-out) and others, Salmela-Aro et al. (2016b) demonstrated substantial differences in student momentary resources, demands, and engagement across the four profiles and contributes to a rich understanding of engagement in situ yet does not conduct profiles of engagement at the momentary level.

Using profiles to account for the dynamics of a multidimensional construct. The person-oriented approach has an important implication for how we consider engagement, in particular when we consider how to understand engagement as a meta-construct (Skinner, Kindermann, & Furrer, 2009) and how to account for its dynamic nature (Csikszentmihalyi, 1990). Regarding engagement as a meta-construct, we know from both engagement and person-oriented research that engagement can be explained in terms of different patterns among its individual components (Bergman & Magnusson, 1997), in the present case its cognitive, behavioral, and affective components. Because learners' engagement includes cognitive, behavioral, and affective aspects experienced together at the same time, it can be experienced as a combined effect that is categorically distinct from the effects of the individual dimensions of engagement. This combined effect can be considered as profiles of engagement. Past studies have considered profiles of cognitive, behavioral, and affective aspects of engagement. For example, Schmidt et al. (advance online publication) demonstrated how ESM and the person-oriented approach can be combined to learn about engagement in terms of how cognitive, behavioral, and affective engagement are experienced at once, and how they exhibit differences across activities and learners' reports of the choices related to the activity that they were able to make. Note that while the person-oriented approach considers the relations among variables together and at once in the experience of learners, they can also be used as part of variable-oriented analyses, and in particular analyses that account for how responses are nested within students, as in repeated measures and longitudinal sources of data.

To account for the dynamic nature of engagement, some past studies have used other measures to predict engagement, such as use of in-the-moment resources and demands (Salmela-Aro et al., 2016b) or, in the case of the study reviewed in the previous section, use of instructional activities and choice (Schmidt et al., advance online publication). For example, Schmidt et al. explored how in the case of laboratory-related activities—especially those that learners perceived as offering them greater choice in the goals of the activity—were associated with more optimal profiles of momentary engagement. Using a person-oriented approach and the use of profiles of cognitive, behavioral, and affective engagement, this study suggests that laboratory related activities akin to those characterized by work with data in which learners have to make choices about how to carry out the analysis may be important predictors of engagement. Another potential way to account for the dynamics of engagement is to consider both engagement and its conditions at once. Since a person-oriented approach emphasizes the dynamic nature of development and the impact of not only external but also intra-individual factors, momentary factors such as resources and demands, could be used along with the measures of engagement to construct momentary profiles.

2.7 Need for the Present Study

While many scholars have argued that work with data can be understood in terms of the capabilities learners develop and the outcome learners achieve, there is a need to better understand learners' experiences working with data. The present study does this through the use of contemporary engagement theory and innovative methodological and analytic approaches. Doing this can help us to understand work with data in terms of learner's experience, which we know from past research impacts what and how students learn (Sinatra et al., 2015), yet which has not been brought to bear on the topic of engagement in work with data. In particular, the use of ESM and a person-oriented approach allow us to study engage in a way aligned with how scholars have recently considered engagement, namely, as something that is dynamic and as something that is multifaceted, including multiple dimensions of engagement and the (subjective and instruction-related) conditions that support engagement. Knowing more about students' engagement can help us to design activities and interventions focused around work with data that are more engaging and which provide more support to learners in terms of their perceptions of challenge and their own competence. While other lenses can be brought to bear to better understand—and support—engagement in work with data, contemporary engagement theory not only has the power to explain differences in how students engage in data modeling, but it also aligns with how both teachers and recent curricular standards consider engagement.

In addition to this general need to study engagement in work with data from the perspective of contemporary engagement theory, no research that I am aware of has examined work with data or data analysis more generally in the context of outside-of-school programs. These settings are potentially rich with opportunities for highly engaged learners to analyze authentic data sources. Third, little research has examined how data is part of the experiences of youth in out-of-school-time programs, despite its place as one of a few core practices in STEM. Fourth, this study employs a data analytic approach that allows for accounting for student, program, and momentary impacts on engagement, at this time an approach that has only been conducted as part of two studies, Strati et al. (2017) and Poysa et al. (2017). Fifth, most studies of engagement have considered it in terms of the individual components of engagement, rather than in terms of profiles of engagement.

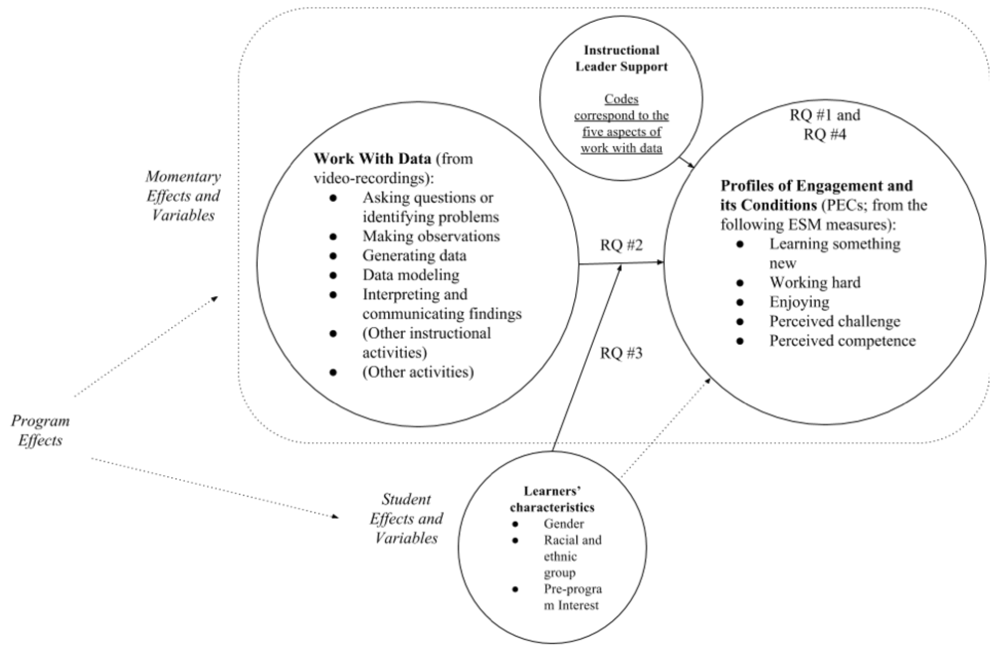

Figure 2.2: A conceptual framework for this study with research questions labeled

2.8 Conceptual Framework and Research Questions

The present study is about how engagement can be used to understand how learners are involved in work with data and how characteristics of activities and learners impact the relationships between work with data and engagement. Its context is out-of-school-time STEM enrichment programs designed to meet guidelines for best practices. The conceptual framework in the present study is presented in Figure 2 and is unpacked in the remainder of this section.

There are five aspects of work with data synthesized from past research (i.e., Hancock et al., 1992; Lehrer & Romberg, 1996; Wild & Pfannkuch, 1999):

1. Asking questions or identifying problems
2. Making observations
3. Generating data
4. Data modeling
5. Interpreting and communicating findings

In this figure, engagement in work with data is associated with different profiles of engagement and its conditions (PECs). The theoretical framework for the person-oriented approach suggests that while the dynamics among the individual aspects of engagement emerge in complex and situation-specific ways, it is possible to consider engagement in terms of patterns among its components. In most settings, a relatively small number of these patterns can be identified in most developmental (and learning-related) settings (Bergman & Magnusson, 1997) and these patterns can be considered in terms of profiles of engagement (Schmidt et al., 2017).

In addition, a pre-program measure of learners' individual interest in STEM is hypothesized to be associated with both the relationship between learners' perception of the activity and themselves and the relationship between the aspects of work with data and engagement because some learners may be inclined from the start to be more engaged. This inclination could explain some of the variability in relations between engaging in work with data and the PECs. ESM responses are associated with students, moments, and program effects that must be accounted for (Strati et al., 2017). Each student in the same program was signaled at the same time, so that each student will have a response associated with each moment (within the same program), and each moment will have a response associated with each student (again, within the same program).

The four research questions are as follows:

1. What is the frequency and nature of opportunities for youth to engage in each of the five aspects of work with data in summer STEM programs?
2. What profiles of youth engagement and its conditions emerge from experiential data collected in the programs?
3. How do data practices relate to youth engagement in the programs?
4. How do youth characteristics relate to their engagement?

Chapter 3

Method

In recognition of the challenge of studying engagement in learning environments where factors related to activities, learners, and each of the nine programs all interact at the same time, this study uses a methodological approach suited to studying engagement as a dynamic, multi-faceted experience. Specifically, this study employs the Experience Sampling Method (ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007) where learners answer short questions about their experience when signaled. This approach is both sensitive to changes in engagement over time, as well as between learners and allows us to understand engagement and how factors impact it in more nuanced and complex ways (Turner & Meyer, 2000).

3.1 Participants

Participants consist of 203 youth. Youth in these programs are from diverse racial and ethnic backgrounds (see Table 1). Most participants are around 13 years old (from youth whose age was available: $M = 12.71$, $SD = 1.70$, $min. = 10.75$, $max. = 16.36$). Detailed demographic characteristics of learners are presented in the table.

3.2 Context

The setting for this study is nine out-of-school STEM programs designed around best practices in urban areas in the Northeast United States during the summer of 2015. These are described in the appendix with pseudonyms for the program names. Two intermediary organizations contracted by the urban area school districts to administer the summer programs. The two intermediaries were responsible for soliciting and enrolling youth; establishing guidelines for the design of the programs, and the goals of the programs; and provide training and professional development for the program's staff. A key difference between the intermediary organizations was that one separated academic and enrichment-related activities, whereas, in another, which was more closely involved in the day-to-day activities of the program, the academic and enrichment components were more integrated, which may have program-specific effects on learners' engagement. Many of the programs aim to involve learners in work with data. These learning environments bring together youth activity leaders, educators, and those with technical expertise in STEM domains. Youth spent around three hours per day for four days per week for the approximately four-week programs, which were taught by youth activity leaders and scientists, engineers, and other community members with technical expertise.

Table 3.1: Demographic characteristics of youth

Youth	Percentage
Sex	
Male	50
Female	50
Race/Ethnicity	
Hispanic	48
White	6
Black	36
Multi-racial	3
Asian/Pacific Islander	7
Parent Education	
High School or Below	79
Graduated from College (B.A. or B.S.)	21

3.3 Procedure

Youth completed a pre-survey before the program. Youth also completed pre-course surveys of their experience in STEM, intention to pursue a STEM major or career, and questions for other motivation and engagement-related measures. At the beginning of the programs, youth were introduced to the study and the phones used for data collection related to the ESM. ESM data were collected two days each week, for three weeks (weeks 2-4 of the program). In all of the programs, about equal video-recording time was dedicated to classroom and field experiences. This detail is important because programs associated with one of the intermediaries rotated between classroom and field experience days, while the other used the first half of each day for one (i.e., classroom activities) or the other (i.e., field experience days).

Each day, youth were signaled four times. These signals were at the same time for all of the youth within their program, but at different times between programs and between days within programs (with the constraint that no two signals could occur less than ten minutes apart). All of the programs were video-recorded by research team members and on three occasions research team members also recorded detailed field notes on the nature of program activities. So that measures corresponding to the video and ESM data can be matched, videos include a signal from the video-recorder identifying the ESM signal to which youth responded at that point in the video.

In a reflection of the dynamic conceptualization of engagement, this study uses data collected from ESM. As such, learners are prompted at regular intervals to respond to short questions about their perceptions of their engagement and its influencers. Though time-consuming to carry out, ESM can be a powerful measure that leverages the benefits of both observational and self-report measures, allowing for some ecological validity and the use of closed-form questionnaires amenable to quantitative analysis (Csikszentmihalyi & Larson, 1987). Despite the logistic challenge of carrying out ESM in large studies, some scholars have referred to it as the "gold standard" for understanding individual's subjective experience (Schwarz, Kahneman, & Xu, 2009). This approach has the benefit of measuring learners' engagement at a fine grain-size: Changes in the activity on learners' engagement, even within the same session of the program, and changes in how influencers of engagement impact engagement and how the activity may relate to engagement, can be measured.

3.4 Data Sources and Measures

Data sources consist of self-reported ESM measures of engagement and learners' perceptions of themselves and the activity, pre-survey measures of youths' interest, youths' demographic information, and video-recordings of programs.

Table 3.2: ESM measures for profiles of engagement and its conditions (PECs)

Construct	Item.text
Cognitive engagement	As you were signaled, were you learning anything or getting better at something?
Behavioral engagement	As you were signaled, how hard were you working?
Affective engagement	As you were signaled, did you enjoy what you are doing?
Perceived challenge	As you were signaled, how challenging was the main activity?
Perceived competence	As you were signaled, were you good at the main activity?

Table 3.3: Measure for pre-program interest in STEM

Construct	Items.text
Individual interest in STEM	I am interested in science / mathematics / engineering.
	At school, science / mathematics / engineering is fun
	I have always been fascinated by science / mathematics / engineering)

3.4.1 ESM measures of learners' engagement and its conditions for the profiles

Measures for engagement and its conditions were constructed from three ESM responses for engagement and two ESM responses for the conditions of engagement. The three variables for engagement are for learning (for the cognitive engagement construct), working hard (for behavioral engagement), and enjoying (for affective engagement). The variables for the conditions are for perceived challenge and perceived competence. All five items are used to construct PECs. Each of the ESM items consisted of the item text and the following four item response options, of which youth were directed to select one: Not at all (associated with the number 1 on the survey), A little (2), Somewhat (3), and Very Much (4), as presented in Table 3.

3.4.2 Survey measures of pre-interest

Measures of youths' pre-interest are used as youth-level influencers of PECs. In particular, three items adapted from Vandell, Hall, O'Cadiz, and Karsh (2012) were used, with directions for youth to rate their agreement with the items' text using the same scale as the ESM items: Not at all (associated with the number 1 on the survey), A little (2), Somewhat (3), and Very Much (4). The measure was constructed by taking the maximum value for the scales for the different content areas (science, mathematics, and engineering), so that the value for a youth whose response for the science scale was 2.5 and for the mathematics scale was 2.75 would be 2.5. The items are presented in Table 4.

3.4.3 Codes from video-recordings for work with data

Different aspects of work with data are identified from video-recordings with the use of a coding frame with five for each of the aspects of work with data. These codes are developed from the STEM-Program Quality Assessment (STEM-PQA; Forum for Youth Investment, 2012), an assessment of quality programming in after school programs. For the PQA, raters contracted by American Institute of Research (AIR) were trained in the use of the PQA measure during February, 2017. Raters completed a four-hour online training module on the overall PQA tool and then attended an in-person two-day training led by a trainer from the David P. Weikart Center for Youth Program Quality, the tool's publisher, where they learned about the instrument, trained on its use, and then established inter-rater reliability with a master coder. For the STEM-PQA, three of the same raters contracted by AIR to overall PQA measure used the STEM-PQA scored one video segment, for which there were no disagreements on scoring across the four raters on any items. If any of the raters encountered into a situation that was difficult to score, they would all discuss the issue by telephone

Table 3.4: Coding Frame for Work With Data

Code	Description
Asking questions or defining problems	Discussing and exploring topics to investigate and pose questions.
Making observations	Watching and noticing what is happening with respect to the phenomena or problem being investigated.
Generating data	Figuring out how or why to inscribe an observation as data and generating coding frames or measurement tools.
Data modeling	Understanding and explaining phenomena using models of the data that account for variability or uncertainty.
Interpreting and communicating findings	Discussing and sharing and presenting findings.

or more often by email after viewing the video in question and reach a consensus on how to score the specific item. Programs were divided up among all of the raters, so raters coded some of the videos for all of the programs.

Specific details on how the measure aligns with the original STEM-PQA on which this measure is based are presented in the appendix.

3.4.4 Demographic variables used

In addition to the measures described in this section, demographic information for youths' gender and their racial and ethnic group are used to construct demographic variables for gender and membership in an under-represented (in STEM) group; membership in an under-represented group are identified on the basis of youths' racial and ethnic group being Hispanic, African American, Asian or Pacific Islanders, or native American.

3.5 Data Analysis

The steps for both preliminary and the primary analyses are described in this section.

3.5.1 Preliminary analyses

First-order Pearson correlations, frequency, range, mean, skew, kurtosis, and standard deviations are examined for all variables including ESM measures for challenge, competence, cognitive, behavioral and affective engagement, and for the pre-survey measure for interest. In addition, the frequency of the codes for aspects of work with data, and the numbers of responses by youth, program, and moment is examined.

3.5.2 Analysis for Research Question #1

First, the frequency of the codes for work with data (and the composite code) are calculated. Then, to present a qualitative description, all of the segments were coded, moments associated with specific codes were identified and used to provide examples for each of the aspects of work with data.

To code the data, three research assistants were trained for approximately eight hours over four meetings. Then, each research assistant coded all of the segments associated with one of the videos. After the coding was complete, the three research assistants and I met to discuss how well the coding frame and potential sources of disagreement. Then, two coders coded every segment that was coded for at least one of the aspects of work with data. This coding took around 75 hours of coding by the research assistants. After each program, the coders met to discuss potential issues that emerged throughout the coding, and to clarify how they applied the coding frame. As this was open-ended coding with the aim to provide greater detail and context for the findings associated with research questions #2 and #3, establishing reliability among the coders was not carried out. The coders sought to document a) the characteristics of work with data and b) other aspects of the instructional context that impacts student work with data.

3.5.3 Analysis for Research Question #2

3.5.3.1 Background on creating profiles using Latent Profile Analysis (LPA)

This question addresses what profiles emerged from the data. This section first provides fit statistics for models that converged and for which the log-likelihood was replicated are described, followed by a comparison of specific, candidate solutions. At the end of this section, models selected are described in detail. Note that while the posterior probability was used as the outcome, there are two approaches to their use in subsequent analyses. One way is to only use the largest posterior probability, setting the other posterior probabilities to a value of zero; in this way, the uncertainty in the profile assignment is accounted for, but partial assignment to other profiles is not considered in their use in subsequent models. The other way is to use the posterior probabilities for all of the subsequent models. In this analysis, the latter option is used: posterior probabilities are used as-is (i.e., none are assigned to zero), though the former approach was used and was found to yield comparable results.

To answer this question, PECs are constructed using on the basis of five variables: cognitive, behavioral, and affective engagement and learners' perceptions of challenge and competence. Answers to this question will help to understand how the aspects of engagement relate to both one another and to key conditions that influence engagement.

To create PECs, a mixture modeling approach is carried out. Mixture modeling is an approach for identifying distinct distributions, or mixtures of distributions, of measured variables. A type of mixture modeling within a latent variable modeling framework, Latent Profile Analysis (LPA; Harring & Hodis, 2016; Muthen, 2004) is used in this study, in particular, to identify the number and nature of PECs. LPA allows for capturing the multidimensional nature of engagement. From this approach, different parameters - means, variances, and covariances - are freely estimated across profiles, fixed to be the same across profiles, or constrained to be zero. In order to provide results for this research question, the MPlus software (Muthen & Muthen, 2017) was used. While MPlus is powerful and widely-used, it can be very difficult to use as part of complex analyses. One reason for why it is difficult to use is that while it provides an environment for executing model *syntax*, it is not an environment, such as SPSS or R, for statistical computing (i.e., preparing data, processing and presenting results). Because of this, I created with colleagues an open-source tool, tidyLPA (Rosenberg, Schmidt, Beymer, & Steingut, 2018 in the statistical software R (R Core Team, 2018). This package is available on the R Comprehensive Archive Network (CRAN). This software provides wrappers–functions that provide an interface–to MPlus functions via the MplusAutomation R package (Hallquist, 2018). It also provides an interface to open-source functions for carrying out LPA that can be used to compare results to those from MPlus.

LPA can be used to identify common patterns in learners' ESM responses as part of a person-oriented analysis to construct PECs. These profiles make it possible to analyze the multivariate data collected on engagement in a way that balances the parsimony of a single model for all learners with a recognition of individual differences in how learners' experience each of the dimensions of engagement together at the same time. A key benefit of the use of LPA, in addition to likelihood estimation-based fit indices, is probabilities of an observation being a member of a cluster, unlike in hierarchical and k-means cluster analysis, for which an observation is hard classified exclusively into one cluster.

3.5.3.2 Selecting a model on the basis of fit indices and other techniques

As part of LPA, different models that determine whether and how different parameters (i.e., means, variances, and covariances) are estimated. In addition, the number of profiles to estimate must be provided by the analyst. Determining the number of profiles depends on fit statistics (such as information criteria and the entropy statistic) as well as concerns of parsimony and interpretability. In general, the approach to choosing the model is similar to choosing the number of profiles, requiring deciding on the basis of evidence from multiple sources. The models are described in-depth in the appendix.

Profiles are constructed with the five self-reported ESM measures for cognitive, behavioral, and affective engagement and perceptions of challenge and competence. Once this step is carried out, the probability of a response being associated with a profile of engagement and its conditions are used as the dependent variable for subsequent analyses. An interface to the MCLUST software was developed and used to carry out the LPA. The number of profiles are determined on the basis of the log-likelihood and bootstrapped likelihood ratio test, entropy, Akaike Information Criteria, and Bayesian Information Criteria statistics, as well as concerns of parsimony and interpretability. This analysis can help us to understand how patterns in higher or lower levels of the variables used to construct the profiles group together in PECs, providing insight into both how engagement is commonly experienced as a meta-construct as well as how key conditions influence engagement.

First, I examined a wide range of model types (i.e., the parameterization of the model) and the numbers of profiles. Note that six model types are able to be specified. These roughly became more complex, with additional parameters estimated, as the number for the model type increases from one to six.

This step is taken to select candidate solutions to investigate in more detail. In order to carry out this analysis, I followed guidelines recommended by the developers of the MPlus software (Asparouhov & Muthen, 2012; Muthen & Muthen,dfs 2017) as well as those making recommendations about its use (Geiser, 2012). In particular, I set the number of starts to 600 for initial stage starts, and to 120 for the number of starts to be optimized. This means that for each model estimated, 600 random starting values for the parameters were used to initialize the EM algorithm. Of these 600, 120 that demonstrated the lowest log-likelihood were allowed to continue until they reached convergence or the limit for the number of iterations. In order for a model to me considered trustworthy, of these 120 runs, the lowest log-likelihood must be replicated at least one time.

If the log-likelihood is not replicated, then the estimation completed one or more times, but because the same log-likelihood value (and parameter estimates) were not obtained, then the solution can be considered to be “under-identified”, a term used to describe solutions that depend strongly upon minor fluctuations in the data (Asparouhov & Muthen, 2007). Accordingly, these solutions may not represent meaningful values and may not be replicable in light of very small changes to the data; these are not considered as candidate solutions for use in subsequent analyses. If no log-likelihood is obtained for any of the random starts, then the software returns an error; in these cases, the convergence criteria–values that determine when a solution has been obtained–are not met. This may be due to a large number of parameters that are estimated relative to the data, such that the number of iterations that the estimation is allowed to go through are not sufficient to obtain a solution (Asparouhov & Muthen, 2007). Like when the log-likelihood is not replicated, these solutions are not considered for use in subsequent analyses.

For every combination of models one through six and from two through ten profiles, only solutions associated with model specifications 1 and 2 (and among these two solutions, only those associated with particular number of profiles) converged. Thus, only solutions associated with models 1 (the model with varying means, equal variances, and covariances fixed to zero) and model 2 (varying means, equal variances, and equal covariances) are explored in subsequent sections. This suggests that the more complex models were too complex given the systematic variability in the data used for the analysis.

After investigating the general information about a range of model solutions, solutions associated with models 1 and 2 are explored in greater detail, following recommendations associated with mixture modeling (Collins and Lanza, 2009; Geiser, 2012) and the authors of the MPlus software (Muthen & Muthen, 2017) as well as recent peer-reviewed articles (Pastor et al., 2007). For these models, the log-likelihood (LL), a range of information criteria (AIC, BIC, sample adjusted BIC [SABIC], consistent AIC [CAIC]), statistics about the quality of the profile assignments (entropy, which represents the mean posterior probability) are presented.

The information criteria are based on the log-likelihood but take various steps to penalize complex models, and so can be used to directly compare models (i.e., the model with the lowest values for these statistics can be considered to better reflect the underlying properties of the profiles). Simulation studies have suggested that BIC, CAIC, SABIC, and BLRT are most helpful for selecting the correct number of profiles (Nylund, Asparouhov, & Muthen, 2007). For the entropy statistic, higher values are considered better, though scholars have suggested that the entropy statistic not be used for model selection (Lubke & Muthen, 2007).The log-likelihood should not be interpreted directly but is presented in conjunction with the information criteria for context about how each of them differs from the log-likelihood. These are also presented in the figures.

In addition to these statistics, a number of modified likelihood ratio tests (LRTs) are used, as the test statistics associated with unmodified LRT do not follow the distribution that the test is based on (Muthen & Muthen, 2017). These are the Vu-Lo-Mendell-Rubin LRT, Lo-Mendell-Rubin LRT, and the bootstrapped LRT. Of the three, the bootstrapped is considered to be the best indicator of which of two models, one nested (with certain parameters fixed to 0) within the other, fits better, but it is also the most computationally-intensive to carry out (Asparouhov & Muthen, 2012). For each of the LRTs, the test statistic and its associated p-value are provided; a p-value greater than .05 suggests that the model with fewer profiles should be preferred.

3.5.4 Statistical software developed

The MPlus software is used to carry out LPA as part of this study. In order to more flexibly carry out LPA, an open-source tool, tidyLPA (Rosenberg, Schmidt, Beymer, Steingut, van Lissa, & Anderson, 2018), was developed. This tool provides interfaces to both the MPlus software and to the open-source mclust software. In addition to being used as part of this study, this package is provided free of use to other analysts as the first tool dedicated to carrying out LPA as part of the R software. More details on the statistical software developed and included in the Appendix.

3.5.5 Analysis for Research Question #3

Broadly, this question is focused on how work with data, as coded from video-recordings of the programs, relates to the PECs. For the primary results for this question, linear models that account for the cross-classification of the moment and youth are used and for the “nesting” of both within each of the nine programs are used. For the outcome (y variable), the probability of a response belonging to the profile is used; thus, there are six models, for each of the six profiles, for each specification of the predictor (x) variables.

Null models showing the proportion of variance (via the intra-class correlation) are interpreted. The more detailed results (in a table) are presented in the appendix. These are followed by the interpretation of findings related to a more variable-centered approach, namely, correlations between individual aspects of work with data and the composite and the profiles (and the variables that make them up) and individual interest. Finally, results of mixed effects models with the work with data variables added separate and then with the composite for work with data are interpreted and presented.

To answer this question, on how well the aspects of work with data predict the PECs, first, indicators for activities coded for any of the five aspects of work with data and either of the other two activities are used to predict each PEC. Next, how each of the five aspects of work with data, as well as the other activities, predict each PEC are explored. Due to similarity in the mixed-effects models used to analyze data to answer Research question #2 and #3, the data analysis strategy for these steps is described together here. First, the general approach used for specifying the mixed effects is first described, followed by details about how the models are used to provide answers to the specific research questions.

The lme4 R package is used (Bates, Martin, Bolker, & Walker, 2015). All of the models use random effects for learner, momentary, and program effects. Learner and moment can be considered to be crossed with both nested within the program. Because the outcome from LPA is not a hard classification (i.e., an observation is in a profile—or not) but a probability, the outcome is treated as a continuous variable. There are as many models as profiles identified in the preliminary analysis. A bottom-up model-building process (West, Welch, & Galecki, 2014), in which a more complex model is constructed on the basis of and continually compared to a more simple model, is used.

First, null models with only the random parts (i.e., random learner, momentary, and program effects) are specified. Then, the predictors are added to the model with the main effects of the variables added to the null mixed effects model. The main effects are for the aspects of work with data and instructional support for the aspects of work with data as well as individual interest in STEM (as a control variable). Note that the interaction between individual interest in STEM and the aspects of work with data is added in a separate step, as described in the next section. The model with the random effects for the learner, moment, and program and with the direct effects of all the predictor variables is presented below.

Here, the probability of a response being associated with a profile is predicted by the direct effects of indicators for the aspects of instructional support work with data measured at the momentary level, their individual interest in STEM measured at the youth level, and the random learner, moment, and program effects.

The general specification for the models for learner i during moment j in program k is written as [i:

$$For\ learner\ i\ during\ moment\ j\ in\ program\ k : Pr(profile_{ijk}) = Fixed\ parts : \beta_{00}\ +\beta_{01}(Indicator\ fo$$

3.5.6 Analysis for Research Question #4

Research question #4 is focused on how the relationships of work with data differ on the basis of pre-program interest and other youth characteristics. Like for the previous two research questions, linear models that account for the cross-classification of the moment and the youth–and their nesting within the programs–are used. Findings from models with pre interest, gender, and URM status are first presented. Then, models with these variable and the individual aspects and composite of work with data are added and then models with the interaction between these characteristics and the composite.

To answer this question, on how youth characteristics impacts relationships between work with data and the PECs, the direct effects of pre-program interest in STEM, gender, and under-represented minority [URM] status, without other predictor variables, were explored. Then, models with these variables and the composite variable for work with data was specified.These analyses were carried out separately for relations between work with data (on its own, corresponding to the analyses carried out for Research question #3) and work with data with instructional support (for Research question #4). Next, for any specific aspect of work with data that significantly predicts each PEC, the same were carried out, so that the interaction between individual interest in STEM and the specific aspect of work with data are used to predict each PEC. These interactions between individual interest in STEM and the dummy codes for aspects of work with data are added to the model specification for Research question #2.

3.6 Sensitivity Analysis

For observational studies, such as the present study, it can be important to determine how robust an inference is to alternative explanations. One approach to addressing this is sensitivity analysis, which involves quantifying the amount of bias that would be needed to invalidate an inference (hypothetically, this bias might be due to omitted or confounding variables, measurement, missing data, etc.). Using the approach described in Frank, Maroulis, Duong, and Kelcey (2013), I carried out sensitivity analysis for inferences we made relative to our key findings. I used the R package konfound (Rosenberg, Xu, & Frank, 2018). The result, and what is used to interpret and contextualize findings, is a numeric value for each effect that indicates the proportion of the estimate that would have to be biased in order to invalidate the inference: higher values indicate more robust estimates in that the inferences would still hold even if there were substantial bias in the estimate.