Examining youth engagement during learning activities that involve work with data: An Experience Sampling approach

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2018-06-04

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Chapter 1

Introduction

Socializing, working, and even teaching and learning are increasingly impacted by data. These sources of data–either quantitative *or* qualitative–are created by us, for us, and about us. Despite the impacts of data, present opportunities for learners themselves to work with data in educational settings are limited.

Work with data includes broad processes of collecting, creating, modeling data, and even asking questions that can be answered with data. This work, then, is more than just crunching numbers. It is also more than interpreting a figure created by someone else. Rather, work with data is about making sense of phenomena in the world–or solving problems in the world. This focus on phenomena is particularly relevant to those designing and enacting learning opportunities focused on work with data (Lee & Wilkerson, in press; Singer, Hilton, & Schweingruber, 2006; Wild & Pfannkuch, 1999).

Despite not being very widespread, aspects of work with data cut across STEM (Science Technology Engineering and Mathematics) domains: Aspects of work with data are recognized as core competencies across recent curricular documents, particularly the *Next Generation Science Standards* (NGSS Lead States, 2013) and the *Common Core State Standards* (in mathematics; National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010). Both of these standards highlight the role of authentic work work with data.

Past research on work with data has largely been set in mathematics contexts and has focused on mathematical practices, like generating measures of phenomena and creating data models (English, 2012; Lehrer & Romberg, 1996; Lesh, Middleton, Caylor, & Gupta, 2008). There has been some research about work with data in science settings (Lee & Wilkerson, in press; National Research Council, 2012), though this work varies greatly in terms of the nature of work with data (McNeill & Berland, 2017). Findings from this past research broadly suggests that engaging in work with data is powerful in terms of learning both about and how to do mathematics and science. Lehrer and Schauble , summarizing past research on the use of mathematical practices in science contexts, note that work with data “has an exceptionally high payoff in terms of students’ scientific reasoning” (Lehrer & Schauble, 2015, p. 696).

To date, past research shows that using a framework from contemporary engagement theory to characterize students’ experiences has been informative both in research and to practicing educators. Knowing more about how youth engage in work with data is valuable as engagement is a meaningful outcome for STEM learners in its own right (Sinatra, Heddy, & Lombardi, 2015). It may also be an antecedent of changes in other outcomes, such as their well-being, achievement and pursuit of an area of study or career (Wang, Chow, Hofkens, & Salmela-Aro, 2015; Wang & Eccles, 2012). However, research has not examined engagement in work with data. Because engaging in work with data seems to be so potentially beneficial to learners, better understanding the nature of work with data and learners’ engagement in such practices is needed.

The purpose of this study, then, is to examine youth engagement in a variety of learning activities that involve work with data. Engagement is explored in the context of outside-of-school STEM enrichment programs carried out during the summer and work with data is considered in terms of specific aspects identified from past research, such as asking questions and generating and modeling data. Knowing more about how youth engage can also provide a foundation for subsequent work to explore how particular curricula and engaging experiences for youth spark their interest in work with data, including hobbies and occupations related to data science, but also in STEM domains in general.

Chapter 2

Literature Review

The framework for this study is informed by work on STEM-related learning practices, student engagement, and approaches to analyzing complex psychological constructs, like engagement. In this review of literature, I define work with data as a key practice, or learning-related activity, across STEM domains. I also define and justify a multi-dimensional framework for understanding engagement, and then review an approach to analyzing data that is ideal for capturing this multidimensionality.

2.1 Defining Work with Data

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 focus on solving real problems or answering authentic questions–rather than being taught and learned as isolated skills–is an essential part of work with data having the most educational benefits to learners (National Research Council, 2012; see Lehrer and Schauble [2012] Windschitl, Thompson, & Braaten [2018] for excellent, practice, in-depth examples of work with data being used as part of instructional approaches). This approach has primarily been used by mathematics educators, as reflected in its role in statistics curriculum standards (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.

Work with data has been conceived in different ways. For some specific examples from different domains, see Lee and Wikerson's (in press) forthcoming summary report for the National Academy of Sciences and Wild and Pfannkuch (1999), Franklin et al. (2007), and Lehrer and Schauble (2004). Because there is not an agreed upon definition of work with data–particularly across subject area domains (i.e., across all of the STEM content areas)–I focus on the core aspects that scholars have most often included in their conceptualizations of work with data. These core components, synthesized from definitions across studies, are better for understanding work with data across STEM content areas–as in the present study–than the components from specific examples, which were developed for use in only one domain. The aspects of work with data that have been articulated in prior studies are distilled into five key aspects (Figure 2.1) for use in this study. They are:

- *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 phenomena, as well as generating tools for measuring or categorizing
- *Data modeling*: Activities involving use of simple statistics, such as the mean and standard deviation, as well as more complicated models, such as linear models and extensions of the linear model

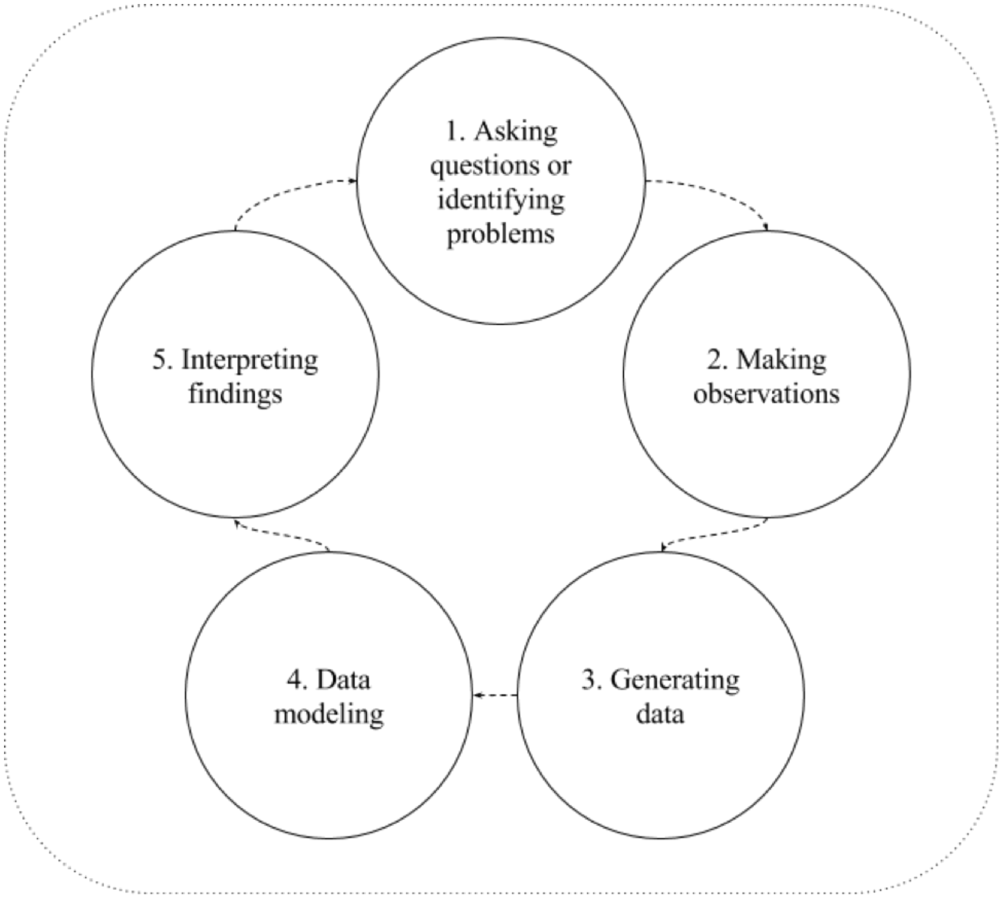

Figure 2.1: Work with data in STEM education settings

- *Interpreting and communicating findings*: Activities related to identifying a driving question regarding the phenomena that the question is about

These five synthesized aspects of work with data are not stand-alone practices but are a part of a cycle. This is not only because each aspect follows that before it, but also because the overall process is iterative: For example, interpreting findings commonly leads to new questions and subsequent engagement in work with data. Also, 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; Lee & Wilkerson, in press).

2.2 The role of working with data in STEM learning environments

Working with data can serve as an organizing set of practices for engaging in inquiry in STEM learning settings (Lehrer & Schauble, 2015). Data are both encountered and generated by learners, and so opportunities for learners to work with data provide many opportunities to leverage their 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 educational 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, even classrooms emphasizing recent science education reform efforts; McNeill & Berland, 2017; Miller, Manz, Russ, Stroupe, & Berland, in press). As a result, 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.

Outside-of-school programs, in particular, 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 open-ended nature of the activities that are possible to carry out during them. Staff, or youth activity leaders, 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 a good context for understanding work with data because little research has examined how data are part of the experiences of youth during them.

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

There is a good amount of past research on cognitive capabilities as outcomes from working 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).

Past research has also shown that there are strategies that can support work with data. These include the design of technological tools and the development of curricula. 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).

Finally, past research has shown 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). Making observations and generating data, 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).

Despite the past research that has been carried out, how learners and youth participate in different aspects of work with data in terms of engagement theory has not been examined. Consider the practice of modeling data, commonly described as a—-or *the*—-key part of many data analyses (Konold, Finzer, & Kreetong, 2017). When modeling data, learners may use data they generated and structured in a data set on their own, or may model already-processed, or use already-plotted, data (McNeill & Berland, 2017). How challenging do students perceive the different enactments of these activities to be and how do learners perceive their competence regarding them? Importantly, how hard are learners working? How much do they feel they are learning? Knowing more about these beliefs, characteristics, and 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.

2.4 Engagement in General and in STEM Domains

In this section, 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, or context-dependent, characteristics and its multidimensional nature. Finally, I describe methods for capturing these two features *empirically* through an approach called the Experience Sampling Method, or ESM, and describe how multidimensional data, collected by ESM, can be analyzed.

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. Engagement is also considered to be changing in response to individual, situation or moment contextual factors, Skinner and Pitzer's (2012) model of motivational dynamics, highlighting the community, school, classroom, and even learning activity, shows the context-dependent nature of engagement on the basis of the impacts of these factors on learners' engagement.

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 achievement-related outcomes, many STEM practices call for engagement in service of other outcomes, especially around epistemic and agency-related dimensions (Sinatra et al., 2015,). For example, many scholars have defined scientific and engineering practices as cognitive practices, which involve applying *epistemic considerations* around sources of evidence and the nature of explanatory processes (see Berland et al. 2016, Stroupe, 2014; Miller et al., in press).

The emphasis on developing new knowledge and capabilities through engaging in STEM practices must be reflected in how the cognitive dimension of engagement is measured. 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. While sometimes defined in terms of extra-curricular involvement or following directions, behavioral engagement is defined in this study as working hard 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).

Finally, there are some key conditions that facilitate engagement. Emergent Motivation Theory (EMT; Csikszentmihalyi, 1990), provides a useful lens for understanding these conditions. From EMT, a key condition for engagement that can change dynamically, from moment to moment, is how difficult individuals perceive an activity to be, or its *perceived challenge*. Another key condition is how good at an activity individuals perceive themselves to be, or their *perceived competence*. What is most important–and necessary in terms of being engaged–is being both challenged by and good at a particular activity.

Past research has supported this conjecture (Csikszentmihalyi, 1990). As one empirical example, Shernoff et al. (2016) demonstrated that the interaction of challenge and competence was associated with positive forms of engagement. These findings suggest that learners' perceptions of the challenge of the activity, and their perceptions of how skillful they are, are important conditions that co-occur with learners' engagement. Conceptualizing perceptions of challenge and competence as conditions, rather than factors that influence engagement, is in recognition of their co-occurrence within individuals, in that youth experience engagement and their perceptions of the activity (perceived challenge) and of themselves (perceive competence) together and at the same time. Thus, these two conditions (challenge and competence) are considered together with engagement in this study, as described in the section below on analyzing multidimensional data on engagement.

2.5 Youth characteristics that may effect their engagement

Past research suggests learners or youths' characteristics, such as their interest in the domain of study, impact their cognitive, behavioral, and affective engagement (Shernoff et al., 2003; Shernoff et al., 2016; Shumow, Schmidt, & Zaleski, 2013). These are both moment-to-moment, context-dependent conditions that support engagement (like those discussed above, perceptions of challenge and competence) as well as youth-specific factors. These factors are at the level of individual differences (i.e., youths' more stable interest in STEM domains), and may impact engagement, as described in this section.

A factor that can support engagement concerns teacher support for specific learning-related practices (Strati, Schmidt, & Maier, 2017). Particularly concerning work with data, which is demanding not only for learners but also teachers (Lehrer & Schauble, 2015; Wilkerson, Andrews, Shaban, Laina, & Gravel, 2016), sustained support from those leading youth activities is an essential component of learners being able to work with data. Thus, how youth activity leaders plan and enact activities related to work with data can have a large impact on students' engagement. Furthermore, because of the importance of work with data across STEM domains, carrying out ambitious activities focused on work with data may plausibly have a large impact on the extent to which youth engage in summer STEM program settings. Consequently, this study considers work with data through the use of a coding frame that characterizes the extent to which teachers are supporting specific STEM practices in their instruction, including aspects of work with data.

Other factors that impact youths' engagement are individual characteristics and differences. 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. Knowing about whether and to what extent youths' interest *before* participating in summer STEM programs explains their engagement *during* them is a key question on its own right. It is also important in terms of properly understanding the effects of other factors, such as working with data, above and beyond the effect of pre-program interest. In addition to this interest, gender and the racial and ethnic group of students is also considered, as past research has indicated these as factors that influence engagement in STEM (Bystydzienski, Eisenhart, & Bruning, 2015; Shernoff & Schmidt, 2008). To include the racial and ethnic group of students, being part of an under-represented minority (URM) group is considered. To sum up, youths' pre-program interest, gender, and URM group membership are considered as individual factors that may impact youths' engagement.

2.6 Challenges of Measuring Engagement as a Contextually-Dependent and Multidimensional Construct

Because of the way engagement has been thought of as having context-dependent characteristics and being multi-dimensional, it is challenging to use engagement (when conceptualized in such a way) in empirical studies. One methodological approach that has benefits in terms of both the context-dependent and multi-dimensional nature of engagement is the ESM. A number of scholars have explored or extolled benefits to its use in their recent work (e.g., Strati et al., 2017; Turner & Meyer, 2000; Sinatra et al., 2015).

This study employs the Experience Sampling Method (ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007) where learners answer short questions about their experience when signaled. ESM involves asking (usually using a digital tool and occasionally a diary) participants short questions about their experiences. ESM is particularly well-suited to understanding the context-dependent 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).

The ESM 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).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).

Research has shown us how the use of ESM can lead to distinct contributions to our understanding of learning and engagement. This work also suggests how ESM can be put to use for the purpose of the present study. For example, 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 (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 that ESM can be used to understand fine-grained differences in learning activities, such as the aspects of work with data that are the focus of this study.

Other research shows us that there are newer approaches to analyzing ESM data that can contribute insights into the context-dependent nature 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 context-dependent nature 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 context-dependent nature of engagement and that such an approach may be able to be used to understand engaging in work with data. Additionally, these recent studies (particularly the study by Strati and colleagues) 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 the analysis of ESM data.

One powerful and increasingly widely used way to examine context-dependent constructs, such as engagement, is the use of *profiles of*, or groups of variables that are measured. This profile approach is especially important given the multidimensional nature of engagement. In past research, profiles are commonly used as part of what are described as person-oriented approaches (see Bergman & Magnusson, 1997), those used to consider the way in which psychological constructs are experienced together and at once in the experiences of learners. Note that in the present study, ESM involves asking youth about to report on their experience at the time they were signaled (rather than, for example, before or after the program, which traditional surveys are well-suited for).

In this study, *profiles of engagement* are used in the service of understanding how students engage in work with data in a more holistic way. There are some recent studies taking a profile 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, 2018), though none have done so to study youths' engagement in work with data.

The profile approach has an important implication for how we analyze data collected from ESM about youths' engagement, in particular when we consider how to understand engagement as a multi-dimensional construct, and one with momentary, or instructional episode-specific, conditions (Csikszentmihalyi, 1990). We know from past 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, to account for the context-dependent 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) and the use of instructional activities and choice (Schmidt et al., 2018). A potential way to extend this past research is to account for not only engagement (cognitive, behavioral, and affective), but also its key conditions (challenge and competence). This is especially important since a profile approach emphasizes the holistic nature of engagement and the impact of not only external but also intra-individual factors. Accordingly, youths' perceptions of the challenge of the activity and of their competence at it are used along with the measures of engagement to construct profiles of engagement. Thus, the profiles of engagement include youths' responses to five ESM items for their cognitive, behavioral, and affective engagement and their perceptions of how challenging the activity they were doing is and of how competent at the activity they are.

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). Knowing more about students' engagement can help us to design activities and interventions focused around work with data. In addition to this need to study engagement in work with data through the lens of engagement, no research has yet examined work with data in the context of summer STEM programs, though such settings are potentially rich with opportunities for highly engaged youth to analyze authentic data sources.

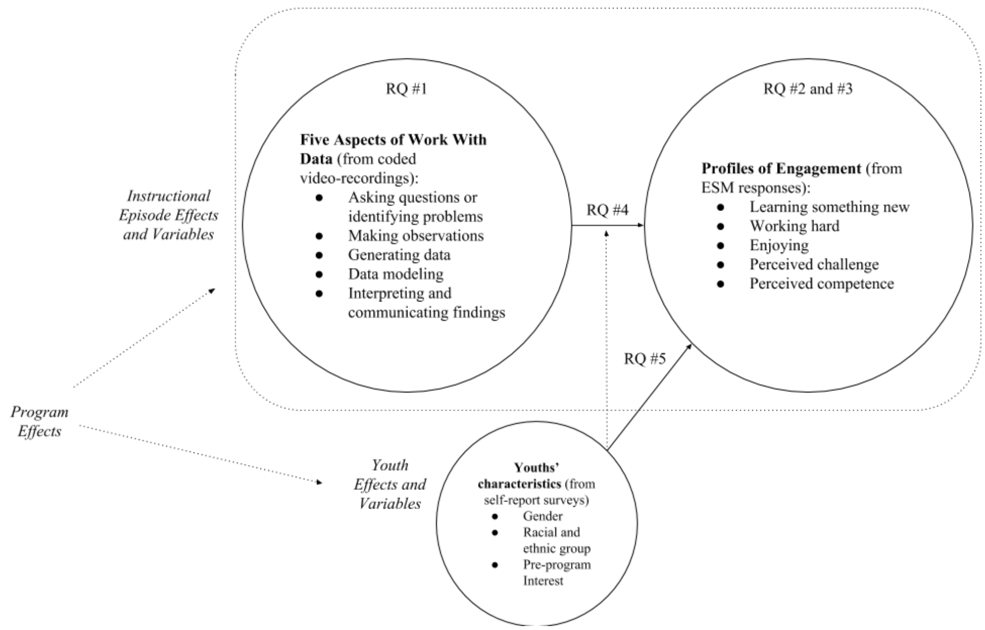

Figure 2.2: A conceptual framework for this study and research questions

2.8 Conceptual Framework and Research Questions

To sum up, the present study is about how learning activities involving various aspects of work with data can be understood in terms of 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 2.2 and is laid out 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 Figure 2.2, engagement in work with data is associated with different profiles of engagement. The theoretical framework for the profile approach suggests that engagement is a multi-dimensional construct consisting of cognitive, behavioral, and affective dimensions of engagement and perceptions of challenge and competence. In addition, a pre-program measure of youths' pre-program interest in STEM, along with youths' gender and URM status, are hypothesized to be associated with the profiles and the relations of work with data and the profiles.

In reference to research questions 2-5, the ESM responses that make up the profiles are associated with different "levels." These *levels*, or groups, which may introduce dependencies that violate statistical assumptions of the independence of the responses, are commonly considered in the Hierarchical Linear Modeling (also known as multi-level or mixed effects modeling) literature as *random effects* (Gelman & Hill, 2007; West, Welch, & Galecki, 2015). In this study, there are three levels that can be modeled as random effects to account for the dependencies they introduce: Youth, instructional episode (which are indicators for the moments–or segments–in which youth are asked to respond to the ESM signal), and the program. Thus, these are not predictor variables, but rather are levels present given the approach to data collection and the nature of the sample. Interpreting their effects is not a goal of this study, but accounting for them in the models used, as in this study, is important and and is done via random effects.

Pre-program interest, gender, and URM status are predictor variables at the youth level. The aspects of work with data are predictor variables at the instructional episode level. There are no predictor variables at the program level, in part due to the small number of programs (and the resulting low statistical power of any variables added at this level). To summarize, pre-program interest, gender, and URM status, and the aspects of work with data are used as predictor variables, while the three levels (youth, instructional episode, and program) are accounted for in the modeling strategy.

The five research questions, then, are:

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 sources of variability are there for the profiles of engagement?
3. What profiles of engagement emerge from data collected via ESM in the programs?
4. How do the five aspects of work with data relate to profiles of engagement?
5. How do youth characteristics relate to profiles of engagement?

Chapter 3

Method

3.1 Context

The setting for the present study was nine out-of-school STEM programs during 2015 in the Northeast United States. Two *intermediary organizations* which were contracted by the local 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 providing training and professional development for the staff, hereafter referred to as youth activity leaders.

There was a difference between the two intermediary organizations, namely, one *separated academic and enrichment-related activities*, whereas, in the other, the *academic and enrichment components were more integrated*, which may have program-related effects on youths' engagement. Many of the programs aim to involve youth 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.

3.2 Participants

Participants consisted of 203 youth. Participants were from diverse racial and ethnic backgrounds (see Table 3.1). The mean age of participants was 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 youth are presented in Table 3.1.

3.3 Procedure

Before the start of the programs, youth completed a pre-survey that included questions about their experience in STEM, intention to pursue a STEM major or career, and 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. As indicated in the earlier section, ESM is a method of data collection that involves asking youth to respond to short questions on phones (that were provided as part of the study). In particular, youth were signaled at random times (within intervals, so that the signals were not too near or far apart) in order to obtain a sample of their experience throughout the program. 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

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

was dedicated to classroom and field experiences. This detail is noteworthy 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 and the second for the other. 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).

The programs were video-recorded by research team members on the days during which ESM data were collected. So that the measures relating the video-recording and ESM data can be matched, the videos included a signal from the video-recorder that identified the ESM signal to which youth responded.

3.4 Data Sources and Measures

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

3.4.1 ESM measures of engagement for the profiles

Measures for engagement were created from five ESM questions, three serving indicators for the experience of engagement and two for the conditions of engagement. The three indicators for engagement were 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 ultimately used to construct the profiles of engaged. 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; 1), A little (2), Somewhat (3), and Very Much (4), as presented in Table 3.2. Note that because these items are measured using single-item indicators (which is common in studies using ESM; Hektner et al., 2007), information about the reliability and validity information for these measures is not included.

Table 3.2: ESM measures for profiles

Construct	Item
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?

3.4.2 The five key aspects of work with data

Different aspects of work with data are identified from video-recordings. Specifically, codes for work with data were generated on the basis of the activity that the youth activity leaders were facilitating. The activity youth activity leaders were facilitating were from the STEM-Program Quality Assessment (STEM-PQA; Forum for Youth Investment, 2012), an assessment of quality programming in after school programs. I then identified the specific activities that corresponded to the five aspects of work with data, as defined in Table 3.4. Details on the reliability of this measure is described next; more information on how the measure aligns with the original STEM-PQA on which this measure is based are presented in Appendix A.

Raters contracted by American Institute of Research (AIR) were trained in the use of the Program Quality Assessment tool (PQA)–the broader assessment tool for which the STEM-PQA is a supplement. 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 code the (overall) PQA measure used the STEM-PQA supplement to score one video segment, for which there were no disagreements on scoring for any of the items. The programs were divided up among all of the raters, so raters coded some of the videos for all of the programs. When the raters encountered a situation that was difficult to score, they would all discuss the issue by telephone or more often by email after viewing the video in question and reach a consensus on how to score the specific item. Note that these codes were unique to each signal to which youth responded (but were not unique to each youth, as youth in the same program were signaled at the same time).

Table 3.3: Coding Frame for Work With Data

Code	Description
Asking questions	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.

Table 3.4: Measure for pre-program interest in STEM

Construct	Items.text
Pre-program 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)

3.4.3 Survey measures of pre-interest in STEM

Measures of youths' pre-interest are used as youth-level characteristics that predict the profiles of engagement. 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). Reliability and validity information on this scale is presented in Vandell et al. (2008).

This 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 2.75. See Beymer, Rosenberg, and Schmidt (2018) for more details on this (taking the maximum value) measurement approach. The items are presented in Table 3.3. Overall levels of this measure were high ($M = 3.044$ ($SD = 0.901$).

3.4.4 Other youth characteristics

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

3.5.1 Preliminary analyses

Correlations (first-order Pearson) and the frequency, range, mean (M), and standard deviation (SD) are first presented for all variables. In addition, the frequency of the codes for aspects of work with data and the numbers of responses by youth, program, and instructional episode are presented. Note that out of the 248 instructional episodes, 236 were code-able for work with data; for the 12 that were not codeable, issues with the video-recordings were the primary source of the missing data. These 236 responses are used for all of the analyses.

3.5.2 Analysis for Research Question #1 (on the frequency and nature of work with data)

There were two primary steps taken to answer this question, one more quantitative in nature and one more qualitative. The quantitative aspect focused on the frequency of work with data, whereas the qualitative aspect focused on the specific nature of work with data.

For the quantitative aspect, the codes for the aspects of work with data (described above in the section on the measures) were counted up and presented as a proportion of the number of code-able instructional episodes. As the signals represent a sample of youths' experiences in the programs, results from this analysis provide insight about how often each of the aspects took place during the programs. Note that this coding frame focused on the degree of *instructional support* the activity leaders provided for youth to work with data, thus results from this analysis will show how often support for the different aspects of work with data was provided, though youth may engage in the aspects of work with data to varying degrees.

The frequency of work with data, the focus of the quantitative analysis for this research question, will provide insight into how regular the aspects of work with data are, but not about the ways in which work with data was enacted. For example, qualitative differences in *how* youth were asking questions will not be evident from the codes as they are used. In order to provide more detail in terms of the nature of work with data in summer STEM segments, the data was coded with an open-ended, qualitative approach.

Specifically, three research assistants were trained for approximately eight hours, over the course of four meetings. Then, each research assistant coded all of the segments associated with the videos for a particular. Two coders coded every segment, except for the segments for which the quantitative coding indicated no aspects of work with data were present; instead, for these segments, only one coder coded each segment.

The coders used the following five guiding questions, associated with each of the five aspects of work with data, for the qualitative coding:

- When questioning or defining problems was observed, what types of questions/problems were involved?
- When making observations is coded, what is the focus of observing?
- When generating data is coded, what is being collected or recorded?
- When analyzing or modeling data is coded, what analysis is being done, or what models are used?
- When interpreting and communicating findings is coded, what is being interpreted or communicated?

For all of the guiding questions, the coders also took note of *who* (the youth, youth activity leader, or someone else) was the focus of the aspect of work with data. For example, with respect to interpreting and communicating findings, denoted when youth were sharing the results from a hands-on investigation or when it was the youth activity leader doing so as a summary on the basis of the work youth recently completed.

After coding all of the segments for each program, the coders and I met to discuss potential issues that emerged throughout the coding. The goal of meeting was to address any problems encountered when using the guiding questions and to clarify how they applied the coding frame. After the coding was complete, I then read through all of the codes for all of the segments then made notes associated with each of the five aspects of work with data. I used these notes to write descriptions of the nature of work with data for each of the five aspects. After reading through the qualitative codes and my descriptions of the nature of work with data during each segment, I grouped the descriptions into themes, which I present in the results for this research question. I also used these themes to calculate proportions, which are also presented in the findings for this section. In summary, an open-ended, qualitative coding approach was used to create descriptions of the ways in which each of the aspects of work with data was enacted. This analysis is used to provide insights into the nature of work with data in summer STEM programs.

3.5.3 Analysis for Research Question #2 (what profiles of engagement emerge)

To answer this question, Latent Profile Analysis (LPA; Harring & Hodis, 2016; Muthen, 2004) is used to identify profiles of engagement. LPA allows for capturing the multidimensional nature of engagement through profiles in terms of discovering groups of the ways in which youth experience engagement together and at once.. 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 cluster analysis). 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 these analyses, five variables were included: the three indicators for the experience of engagement (cognitive, behavioral, and affective) and the two necessary conditions for it (perceptions of challenge and competence). In addition, solutions with between two and 10 profiles were considered. As part of LPA, the model type selection–where the type refers to which parameters are estimated–is a key topic. For the present study, six model types were considered:

1. Varying means, equal variances, and covariances fixed to 0
2. Varying means, equal variances, and equal covariances
3. Varying means, varying variances, and covariances fixed to 0
4. Varying means, varying variances, and equal covariances
5. Varying means, equal variances, and varying covariances
6. Varying means, varying variances, and varying covariances

The MPlus software (Muthen & Muthen, 1998-2017) is used to carry out LPA through statistical software I developed, *tidyLPA*. More details on LPA are included in Appendix D.

To select a solution in terms of the model type and the number of profiles to be interpreted and used in subsequent analyses, a number of fit statistics and other considerations were taken into account. These include 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), statistical tests (Vu-Lo-Mendell-Rubin LRT [VLMR], Lo-Mendell-Rubin LRT [LMR], and the bootstrapped LRT [BLRT]), and concerns of interpretability and parsimony are used. On the basis of these criteria, a particular solution is selected and used as part of subsequent analyses; as the model selection process is an integral part of providing an answer to this question, the model and number of profiles selected is described in the section for the results for this research question.

3.5.4 Analysis for Research Question #3 (sources of variability for the profiles)

How youth are engaging is a function of who they are as an individual, what they happen to be doing during a particular instructional episode, and which youth program they are enrolled in, as well as random variation. This analysis seeks to identify how much of the variation is at each of these levels through using null models, or models only with the indicators for the three levels (youth, instructional episode, and program). These models can show how much variability in the profiles is systematic at these different levels and is potentially attributable to each of these types of factors. These null models may also suggest something about where you might want to be looking to explain sources of youth's engagement.

Sources of variability in these profiles can be used as additional information in their own right for interpreting the profiles and in order to anticipate the effects of predictor variables at the youth, instructional episode, and program levels. First, the proportion of the variability at each of these levels is explored through the use of null, or variance components, in Table 4.4. These are models that only include grouping (i.e., the variable identifying which youth a response is from, what signal the response is associated with, and from which program the youth and signal were from) factors. These models provide insight into at which of these "levels" predictors may be able to explain the outcome.

Variability in terms of the number (and proportion) of profiles each youth reports can also be considered. The breakdown of responses in each of the six profiles by youth is used to show the extent to which youth report their most reported profile. In addition, apart from this overall mean proportion of youths' responses, the mean proportion for specific profiles (i.e., when youth report a particular profile the most, how often, on average, do they report it?) are also considered.

The ICCs provide information about sources of variability in the profiles of engagement with respect to the same profile. One way to better understand the nature of variability across profiles is by examining how often youth reported the same profile: Whether youth exhibit stable or highly variables modes of engagement (i.e., are some youth always *Fully* engaged?) can provide a descriptive portrait of youths' experiences the many instructional episodes they were involved in. To determine how stable youths' engagement was, for each youth, the profile that youth reported most was identified, and then the proportion of their responses in that profile was calculated. These proportions are also presented in the results for this question.

3.5.5 Analysis for Research Question #4 (how work with data relates to engagement)

This question is focused on how work with data relates to the profiles of engagement. For the primary results for this question, mixed effects models that account for the cross-classification of the instructional episode (because of the dependencies of the responses associated with each of the 248 distinct ESM signals) and youth are used and for the "nesting" of both within each of the nine programs are used. The *lme4* R package (Bates, Martin, Bolker, & Walker, 2015) is used. All of the models for this and the subsequent research question use random effects for youth, instructional episode, and program effects. Youth and instructional episode can be considered to be crossed with both nested within the program.

The probability of a response belonging to the profile is the dependent variable and the aspects of work with data are the independent variable. There are six models, for each of the six profiles. Because the outcome from LPA is not a hard classification (i.e., an observation is in a profile—or not) but a probability, the dependent variable is treated as a continuous variable.

First, null models with only the random parts (i.e., random youth, instructional episode, and program effects) are specified. Then, the five aspects of work with data are added as predictors to the model. The results will be interpreted on the basis of which of the statistical significance and the magnitude and direction of the coefficients associated with these five predictors. For example, if the coefficient for the effect of the asking questions aspect of work with data upon one of the profiles is 0.10, and is determined to be statistically significant, then this would indicate that when youth are engaged in this aspect of work with data, then they are ten percentage points more likely to report a response in that particular profile.

For this question, models with the aspects of work with data both separate from and together with the youth characteristics were fit. The models with both together were also used as part of research question #4, though they are presented here (and interpreted in the sections for both results). In specific, mixed effects models, predicting the probability of membership in each of the six profiles as the dependent variable–using the work with data codes as predictors–were specified.

Because the results were found to be identical when the aspects of work with data and the youth characteristics are considered in separate and in the same model, the results from the two sets of variables being in the same model are used for both to provide answers to both this and the next research question. Note that a composite for work with data (made as the sum of the individual aspects of work with data) was considered, but as it did only yielded one (small) statistically significant result, the results for this analysis are not presented in the results.

3.5.6 Analysis for Research Question #5 (how youth characteristics relate to engagement)

This question is focused on how the relationships of work with data differ on the basis of youth characteristics. In particular, their pre-program interest, gender and URM status are used as predictor variables. The same (mixed effects) models (and statistical software) used for the previous research question are used for this research question. The dependent variable is again the probability of a response being in the profile.

The three youth characteristics (pre-program interest in STEM, gender (entered s a dummy code with the value of "1" indicating female), and URM status (also entered as a dummy code, with "1" indicating a youth from a URM group) are added as predictors. Like for the previous research question, the statistical significance and the magnitude and direction of the coefficients associated with each predictor are interpreted to answer this question. For example, and similar to the interpretation of the predictors associated with RQ #3, if the relationship between pre-program interest and a profile is 0.05, then for each one-unit increase in pre-program interest, then youth are are five percentage points more likely to report a response in a particular profile.

Models with the youth characteristics separate from and together with the aspects of work with data were fit. Like for the results for the previous question, the models only with the youth characteristics yielded very similar results. Thus, the models presented in the previous section with both youth characteristics and the aspects of work (see the table above) with data are interpreted here.

As described in the previous sub-section, because the results were very similar when the aspects of work with data and the youth characteristics were added in *separate* models compared to when they were included in the same model, the results for both sets of predictors in the same model are presented and interpreted. In addition, interactions between statistically significant aspects of work with data and all of the youth characteristics are examined, though because none of these interactions were found to be statistically significant, they are not included with the results.

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. Using the approach described in Frank, Maroulis, Duong, and Kelcey (2013), I carried out sensitivity analysis for inferences made relative to key findings. I used the R package konfound (Rosenberg, Xu, & Frank, 2018).

The result of the sensitivity analysis, and what is used to interpret and contextualize findings, is a numeric value, between 0 and 1, for each effect that indicates the proportion of the estimate that would have to be biased in order to invalidate the inference. Value close to 0, such as .05, indicate that a very small change in the size of the effect would change the inference made (i.e., a statistically significant result that is interpreted would no longer be interpreted as an effect). Larger values, such as values around .50, indicate that a substantial amount of an effect could be due to bias (i.e., less than 50% of an effect could be due to bias in the sample), but even still, the same inference about a statistically significant could be made, suggesting that such an effect is more robust than one with a smaller value.

I use sensitivity analysis to interpret and contextualize hypotheses about key relationships for research questions #4 and #5 for this study, for the relationships between the aspects of work with data and youth characteristics and the profiles of engagement. In particular, I carry out sensitivity analysis for the coefficients that are statistically significant in order to provide some insight into how robust the results are. In addition, I carry out sensitivity analysis for coefficients that are close to statistically significant but are not statistically significant, in order to better understand just how little would need to change in order for an effect to be determined to be significant. H

higher values from the the analysis (i.e., values closer to 1) indicate more robust estimates in that the inferences would still hold even if there were substantial bias in the estimate and that are interpreted as robust findings, while lower values, when present, indicate less robust findings that I interpret with more caution.

Chapter 4

Results

4.1 Preliminary results

4.1.1 Descriptive statistics for the engagement measures

First, descriptive statistics for the engagement measures (the five variables that were used to estimate the profiles) are presented in Table 4.1. These descriptive statistics show high overall levels of the three indicators of engagement (with mean values on scales that ranged from one to four between 2.768 (SD = 1.063) for cognitive engagement, and 2.863 (SD = 1.044), for behavioral engagement). These statistics also show high perceptions of competence (M = 3.000 (SD = 0.952)) and more moderate perceptions of challenge (M = 2.270 (SD = 1.117)). There was a similar degree of (moderate) variability (see the *SD*s) across the five measures, indicating that, across all of the ESM responses, engagement was not the same (due to the youth, instructional episode, program, and for unexplained reasons).

4.1.2 Correlations among the study variables

Next, correlations between the variables that are used to create the profiles of engagement are presented (Table 4.2). These correlations, which range from r = .08 through r = .60 (all statistically significant), reveal low to moderate relations among these variables.

Table 4.1: Descriptive statistics for study variables

	n	Mean	SD
Cog. eng.	2969	2.768	1.063
Beh. eng.	2959	2.863	1.044
Aff. eng.	2970	2.831	1.051
Challenge	2970	2.270	1.117
Competence	2970	3.000	0.952

Table 4.2: Correlations among study variables

	Pre-interest	Cog. eng.	Beh. eng.	Aff. eng.	Challenge	Competence
Pre-interest						
Cog. eng.	.14					
Beh. eng.	.13	.60				
Aff. eng.	.12	.59	.57			
Challenge	.15	.30	.27	.27		
Competence	.06	.40	.41	.47	.08	

Table 4.3: Proportion of signals for which each of the aspects of work with data was present

Aspect of Work With Data	Proportion	N
Asking Questions	0.381	90
Making Observations	0.242	57
Generating Data	0.432	102
Data Modeling	0.288	68
Communicating Findings	0.436	103

4.2 Results for Research Question #1

4.2.1 Frequency of the aspects of work with data

Of the 236 instructional episodes used in the analysis, 170 (72%) of them were coded as involving *any* of the five aspects of work with data. As presented in Table 4.3, the five aspects of work with data occurred regularly. Making observations was found to be the least frequent of the five aspects, occurring in 24% of instructional episodes. Data modeling was the next most frequency, occurring in 29% of the episodes, followed by asking questions (38%), generating data (43%), and communicating findings (again 43%).

Note that these results are for the codes for the (approximately ten-minute, video-recorded) instructional episodes, and that the aspects of work with data *can* (and *did*) co-occur: On average, there were 1.86 (SD = 1.61) aspects of work with data present during each instructional episode. This indicates that, on average, youth were engaged in around two of aspects of the work with data during each instructional episode. There was a considerable amount of variation in the extent to which these types of work with data were supported in each program: In Appendix C, the frequencies by program are presented.

4.2.2 The nature of work with data

The open-ended, qualitative approach used to understand the specific nature of youths' work with data showed there to be distinct ways in which youth worked with data. Note that for each aspect of work with data, the percentages of the themes do not sum to 100% as many instructional episodes involved the presence of the aspect of work with data in ways that were not very common and systematic.

4.2.2.1 Asking questions or identifying problems

Among the instructional episodes that involved asking questions, qualitative descriptions revealed that around one-third (36/92, or 39%) explicitly demonstrated youth working to understand the phenomenon or problem they were investigating. When doing so, they were focused on actively constructing predictions and hypotheses about phenomena related to the program. For example, in an instructional episode during the *Ecosphere* program in which youth constructed inclined tables to study how water moved throughout the ecosystem, the youth activity leader prompted youth to generate hypotheses of what would happen when water was poured onto the table, before pouring the water.

Other instructional episodes involved questions that were not focused on predicting or hypothesizing, but rather on asking a more general type of question (21/92; 23%), or involved the *instructor* (but not youth) posing questions or identifying problems (14/96; 16%). In the former case, youth were found to be asking generic questions about understanding the assignment, task, or even the phenomena. For example, in the *Marine Investigators* program, youth visited a water treatment site, and were provided opportunities to ask questions about what they observed: However, youths' questions were not questions that could then be answered with empirical data, but were rather to clarify their understanding. In the latter, instructors were asking youth questions (i.e., math-related prompts or questions to elicit their conceptual understanding).

4.2.2.2 Making observations

In the instructional episodes when the STEM-PQA revealed that youth were making observations, the vast majority (49/57, 86%) of these were focused on observing phenomena in the field, or, in the case of engineering-focused programs, noticing what was going on with a particular design. For example, in the *Building Mania* program, youth constructed Rube Goldberg machines; youth were prompted by the activity leaders to notice how changes in their design led to differences in how far objects were launched or rolled.

Sometimes, while youth did make observations of phenomena, they faced the challenge of using that data in subsequent activities and through engaging in other aspects of work with data. For example, the science-focused programs (*Island Explorers*, *The Ecosphere*, and *Marine Investigators*) all emphasized making observations, but these observations were not frequently written down or entered into a spreadsheet as data. For example, in *Marine Investigators*, youth observed how the Atlantic Ocean brings salt water into the (freshwater) bay. Youth observe "buffers" between the salt and freshwater, but do not collect or otherwise generate data related to their observations.

In a small number of cases making observations were focused on making observations not of phenomena, but of something more general (10/57; 18%). For example, in the *Adventures in Mathematics* program, youth observed other youth or the activity leader working through a mathematics problem, but not one that at any stage of the activity was focused on a phenomena that youth identified or discussed.

4.2.2.3 Generating data

In about half (48/102; 47%) of the episodes that involved generating data, youth were writing down their own observations of a phenomenon, recording information from experiments, or recording the results of a trial (in engineering contexts). For example, in the *Marine Investigators* program, youth collected pieces of recyclable plastic, bringing them back to the classroom and counting them for each location they were collected.

During some of these cases, youth generated data, but they did not use the data they generated in subsequent activities. In the engineering-focused programs (*Uptown Architecture*, *Crazy Machines*, and *Dorchester House* particularly, youth often generated data that resulted from their engineering designs (and communicated and interpreted their findings,) but did not model this data as a regular part of their activities. In one particular example, in the *Ecosphere* program, youth collected water samples in the field. They then brought these samples to the classroom and tested the water, involving youth in both collecting and, to a degree, generating data (by noting the pH levels of the water). However, later in the day, youth created a small-scale model (with inclined trays of dirt, rocks, and plants) of an ecosystem, in which they added food coloring to determine the impacts of chemicals and acid rain. Youth then interpreted and discussed these findings, but did not connect the discussion to the water samples youth collected and tested earlier.

In a very small number of cases (2/102; 2%), youth collected, but did not write down data. For example, again in the *Marine Investigators* program, youth used nets to collect saltwater organisms, which they then transported in buckets back to the classroom setting for subsequent analysis. While these specimens were collected to serve as data for a future activity, there was no recording observed during the episode. Very often, in the (approximately) other half of episodes related to this aspect of work with data, the ways in which youth generated data were not very systematic or clearly identifiable, a point discussed in detail in the next chapter.

4.2.2.4 Data modeling

A large majority (49/68, 72%) of the instructional episodes coded (with the STEM-PQA) for data modeling were focused on youths' uses of statistical and mathematical models. For example, in the *Comunidad de Aprendizaje* program, youth accessed nationally-representative data and were tasked to solve problems, like finding out what percentage of people engage in particular activities, like donating to charity. In another example, in the *Marine Investigators*, youth participated in activities designed to help them understand water quality in their ecosystem. Youth collected trash from sites around their community (in different "districts") and then brought the trash and recyclable plastic back to the classroom. Then, the youth activity leaders involved youth in an ambitious data modeling activity. The aim was to figure out how much plastic enters local waterways. As a part of this activity, youth activity leaders asked youth not only to determine the quantity of trash that entered the waterways, but asked youth about *why* youth thought about and used math in particular ways (i.e., by adding the quantity of trash collected and then extrapolating from this quantity to the amount from across the entire city over the course of the year). This appeared to be an ambitious and powerful data modeling activity.

Very often, data modeling was focused on solving equations, even when related to real-life (as in buying groceries, how money is spent, and how to budget, in *Comunidad de Apendizaje*). In these episodes during which youth were modeling data (4/68; 6%), they were using equations provided by the youth activity leader to solve problems. When data modeling, a model was not always one of data. In a small number of the cases (5/68; 7%), the model was a physical model, such as during the *Crazy Machines* program, in which youth saw how changes to their Rube Goldberg machine worked or did not work.

While data modeling activities appeared to be ambitious in their design and enactment, youth activity leaders sometimes faced the challenge of linking data modeling activities to other aspects of work with data. For example, the mathematics-focused programs, such as the *Adventures in Mathematics* program, the youth activity leaders recognizing that youth had difficulty solving equations, used duct tape and building on an earlier activity in which youth considered what constituted a rate, on how many "hops" it would take someone to move from one end of the line of duct tape to the other. The youth activity leader than asked youth to consider how far they could move in one hop and to consider how they could find out many hops it would take, using a mathematical equation. In this activity, youth were supported in their attempts to approach mathematics problem-solving in creative ways.

In a small number of instructional episodes, data modeling involved a model that could generate data (6/68; 9%). For example, in the *Marine Investigators* program, a youth activity leader used a plush toy seal designed to teach youth about anatomy and the dangers of aquatic mammals consuming trash and recyclables. In this specific instructional episode, a model was clearly used (by the youth activity leader rather than the youth, in this case), but the model was not a data model but rather a physical one that was used to help youth understand a phenomenon.

4.2.2.5 Interpreting and communicating findings

In around half (49/103, 48%) of the instructional episodes in which youth were interpreting and communicating findings (as coded by the STEM-PQA), youth were sharing what they found from an investigation or the results of using the product they designed. For example, in the *Comunidad de Aprendizaje* program, youth participated in an activity designed to support their thinking about creating a product to bring to market; the youth activity leaders described this as being akin to the television show the *Shark Tank*. In one instructional episode, the youth activity leader asks youth to think of an idea that would make an investor willing to invest in; youth shared their ideas, describing what their ideas was, why it was a good idea, how much they could sell it for, and what their profit would be, while fielding questions from youth activity leaders and their peers. Interpreting and communicating findings was also commonly present in instructional episodes in which youth were debating the findings of an investigation, such as the results of calculations for the amount of recyclables entering waterways (in *Marine Investigators*).

In the other instructional episodes that were not focused on youth sharing what they found from an investigation, youth were most commonly communicating about topics other than the results of an investigation or design process (3/103, 3%), such as trying to find out the answer to a discrete question posed by the youth activity leader, or the youth activity leader was who was doing the interpreting and communicating (4/103, 4%). For example, in the former case, during the *Adventures in Mathematics* program, the youth activity leader helped youth to solve problems on a worksheet, asking guiding questions to help them to begin to solve problems on their own. In the latter type of interpreting and communicating findings (the youth activity leader doing the interpreting and communicating), youth commonly engaged in other aspects of work with data (i.e., generating data), but the youth activity leader compiled, modeled, and then interpreted the data that the youth generated, rather than youth doing such activities themselves.

4.3 Results for Research Question #2: What profiles of youth engagement emerge from experiential data collected in the programs?

On the basis of fit statistics, statistical tests, and concerns of interpretability and parsimony, a solution with six profiles was selected for use in subsequent analyses. This solution was associated with a model with varying means, equal variances, and covariances fixed to 0 (the first model type among those described in the methods). Because of the exploratory nature of the approach used to identify the profiles, LPA, it is important to consider alternate solutions. In particular, a seven profile solution with the same model specification was similar (but not superior) in terms of the fit statistics and statistical tests. This solution, presented in Appendix F, was determined to not be superior to the six profile solution, ultimately chosen on the basis of parsimony and interpretability.

The results of this model selection process was the estimation of *six distinct profiles* identified from the data, as presented in Figures 4.1 and 4.2. Figure 4.1 shows the profiles with variables that were centered to have a mean equal to 0 and a standard deviation of 1. Thus, the *y*-axis for this plot is labeled “Z-score”). Figure 4.2 shows the profiles with the raw data (not transformed). Thus, the *y*-axis for this plot is labeled “Value.” The two plots are presented because they provide different insight into the composition of the profiles: Those with the centered variables highlights positive and negative departures from the mean value for each variable, making differences between the profiles distinct. The plot with the raw data instead highlights the reported values of the variables, emphasizing the values of the variables in the profiles in the same units youth considered when they responded (and potentially highlighting similarities that may seem very different in the plot with the centered data).

This solution is characterized by:

- A *universally low* profile, characterized by low levels of working hard, learning something new, and enjoying the activity, and perceptions challenge and competence
- An *only behaviorally engaged* profile, with moderate levels of working hard, very low enjoyment of the activity, and moderately (low) levels of learning something new and challenge and competence
- An *only affectively engaged* profile, with moderate levels of enjoyment, low levels of hard work, and moderately (low) levels of cognitive learning something new, challenge, and competence
- A *all moderate* profile, with moderate levels of the three indicators of working hard, learning something new, enjoying the activity, challenge, and competence
- An *engaged and competent but not challenged* profile, characterized by high levels of working hard, learning something new, enjoying the activity, and competence, but with low levels of challenge

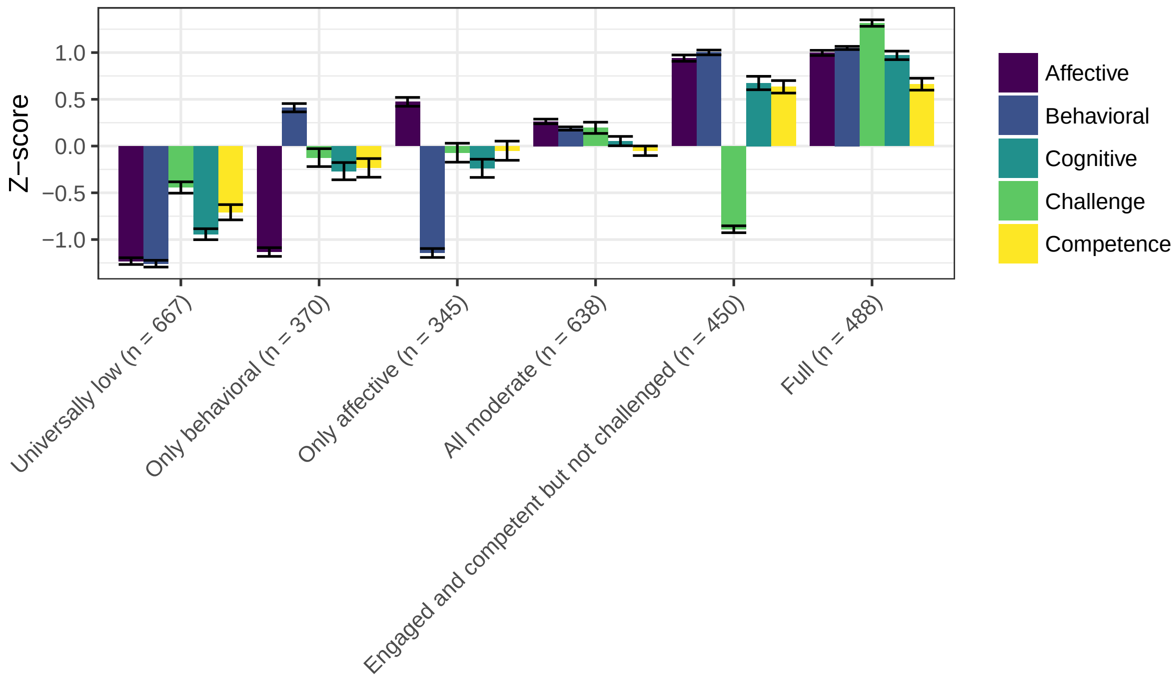

Figure 4.1: The six profiles of engagement (with variable values standardized)

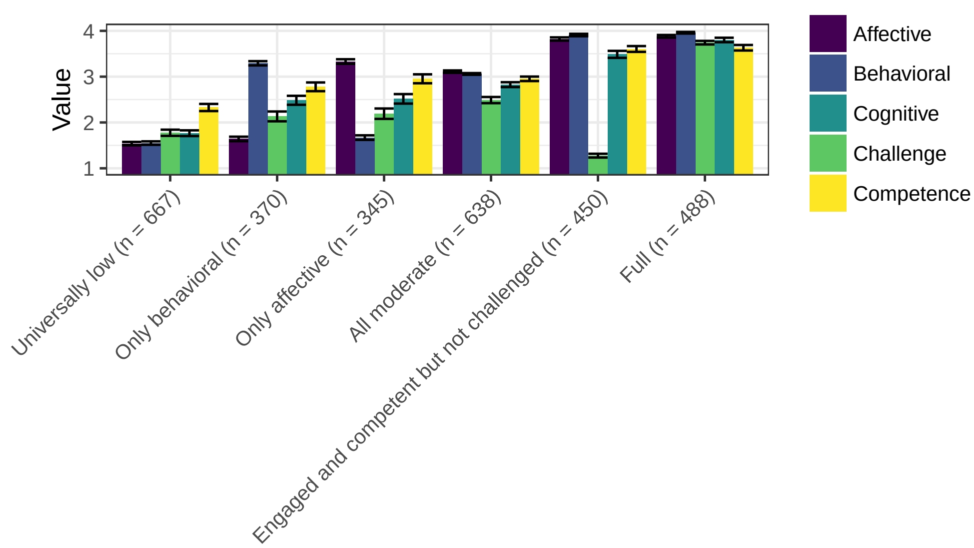

Figure 4.2: The six profiles of engagement (with raw variable values)

Table 4.4: Intra-class correlation (ICC) values for each of the three levels

Profile	Instructional Episode	Youth	Program
Universally low (n = 667)	0.006	0.267	0.023
Only behavioral (n = 370)	0.006	0.093	0.009
Only affective (n = 345)	0.004	0.262	0.003
All moderate (n = 638)	0.015	0.310	0.000
Engaged and competent but not challenged (n = 450)	0.009	0.100	0.000
Full (n = 488)	0.031	0.432	0.019

- A *full* profile, with high levels of working hard, learning something new, enjoying the activity, challenge, and competence

The six profiles are characterized by both varying levels on both the indicators of engagement (cognitive, behavioral, and affective) and perceptions of challenge and competence. In addition, the number of observations across the profiles is relatively balanced (with no profiles associated with a very large or small number of observations). The universally low profile was associated the largest number of observations (n = 667), followed by the all moderate profile (n = 638); each of the other four profiles were associated with 300 to 400 observations. The results for research questions 3-5 use this solution and the six profiles in subsequent analyses.

4.4 Results for Research Question #3: What sources of variability are there for the profiles of engagement?

For all six profiles, the ICCs represent the systematic variability (the proportion of variance explained) associated with each of the three levels (youth, instructional episode, and program) for each profile. Thus, the different levels can have different proportions of variance explained for different profiles: The systematic variability at the youth level, for example, could be .10 for the *Full* profile and .025 for the *Universally Low* profile.

At the program level, the ICCs were found to be small, with values ranging from 0.00 to 0.023, suggesting that little variability can be explained by the program youth were in. For the instructional episode level, the ICCs were also small, ranging from 0.004 to 0.01. Finally, at the youth-level, the ICCs ranged from .093 to .432. Looking across these values, most of the explained variability in the responses is associated with youth; the program and instructional episode levels were associated with very small values, suggesting that variables at the instructional episode may have minimal effects, although adding variables at *other* levels (i.e., youth characteristics that are at the youth level) can change the value of (other levels') ICCs (Gelman & Hill, 2007).

As described earlier, the levels are associated with different ICCs for different profiles. In terms of ICCS at youth level across the six profiles, the value for the youth-level ICC was highest for the *Full* profile (ICC = .432), suggesting that some youth have a strong tendency to be fully engaged (possibly due to their initial interest or other individual characteristics and differences). The other profile characterized by a consistent pattern across all of the variables–the *Universally low* profile–had a modest value for the ICC at the youth level (ICC = .267). Finally, a large amount of variability is associated with the residual (variance that is not associated with the program, instructional episode, or youth levels). This suggests that there is wide variation in youths' responses that may not be readily explained or predicted by variables *at one level alone*. Remaining unexplained variability is captured by the residual term. Some youth from particular programs may engage during some episode instructional episodes in very high or low ways that are not captured by modeling the variability at each of these levels alone.

The ICCs lend insight into the sources of variability for a specific profile. In addition to this analysis,

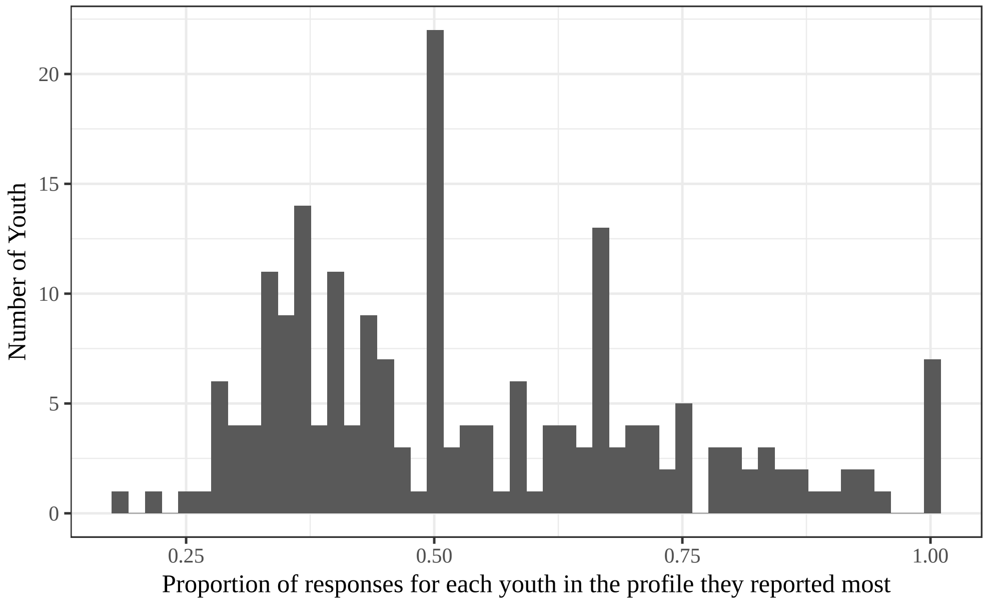

Figure 4.3: Histogram of the proportion of responses for each youth in the profile they reported most

examining how often youth reported the same across instructional episodes lends further insight into sources of variability for the profiles. This analysis can be particularly useful for understanding variability at the youth level, which the ICCs show to be associated with the most systematic variability. As presented in Figure 4.3, the mean proportion of responses for each youth in the profile they reported most varied widely across youth. There was a small number of youth who reported the same profile in all of their responses, but for most youth, the profile they reported most made up only a portion of all of their responses. For most youth, the most frequent profile was observed just over 50% of the time. Specifically, on average, youth reported their most-reported profile in .540 (SD = .194, min = .182, max = 1.00) of their responses.

In sum, these findings show that there was substantial variability in the profiles present at the youth level. Less variability was explained by either the program youth were in or the nature of the particular instructional episode present when youth were signaled. These results set the stage for those for the next two research questions, on the relations between the aspects of work with data (for research question #4) and the youth characteristics (for research question #5) and the profiles of engagement.

4.5 Results for Research Question #4: Aspects of work with data and engagement

As a part of the analysis for this question, six models (one for each profile) were specified. For these models, the probability of a response being associated with one of the six profiles was the dependent variable, and the aspects of work with data were the predictor (or independent) variables. As this question is about how the aspects of work with data relate to the profiles, the coefficients associated with each of the five aspects are interpreted in order to provide results for this research question: While the youth characteristics were included in the same six models, these are interpreted for research question #5. I included both of the two sets of variables in this same models because the results were practically the same whether they were included separate models (i.e., only the aspects of work with data in six models and only the youth characteristics in six models) or the same (both the aspects of work with data and the youth characteristics in the same six models) models.

The results for this and the next research question are both presented in Table 4.5. In this table, each column represents the output from one of the six different models. As an example, the first column in Table 4.5 includes results for the model predicting the probability of a response being associated with the *Only behavioral* profile as the dependent variable. Each other cell in this column contains the coefficients (and their standard errors and asterisks indicating statistical significance) for each of the predictor variables. Note that the p-values are calculated using the most conservative and recommended by recent research *Kenward-Rogers approximation* (Halekoh & Hojsgaard, 2014).

This analysis showed that there were minimal relations between work with data and the profiles. There were only significant relations with the *Full* profile (see the column with the column name *Full* for these results). One relation that was statistically significant was for the relations between modeling data and the *Full* profile ($\beta = 0.034$ (0.017), $p = .020$; *partial* $R\hat{}2 = .002$). This shows that when youth were modeling data, they were around 3% more likely to be fully engaged. In other words, when youth are involved in these activities, they are more likely to report working harder, learning more, enjoying themselves more, and feeling more competent *and* challenged.

Another significant relation was between generating data and the *Full* profile ($\beta = 0.027$ (0.015), $p = .033$; *partial* $R\hat{}2 = .002$): When youth were either modeling or generating data, they were (like for data modeling) around 3% more likely to be fully engaged. To sum up these two findings, modeling data and generating data are associated with a (very) positive form of engagement, that exhibited by the *Full* profile. The effect sizes indicate quite small effects in substantive terms.

To determine just how robust these effects were, sensitivity analysis was carried out for these two effects (for the relation of data modeling with *Full* engagement and the relation of generating data with *Full* engagement). This follow-up analysis revealed that the effect of modeling data on *Full* engagement much more robust than that for generating data: 9.835% of this effect (of data modeling) would have to be due to bias to invalidate the inference about its effect. For generating data, only 1.884% of the effect of generating data would need to be due to bias to invalidate the inference about its effect. These values are not minuscule but are also not very large (Frank, 2003). So, while statistically significant, the effect of data modeling seems to be a more robust effect than the effect of generating data, which does not seem to be a very robust (and should therefore be interpreted with some skepticism).

There was another effect which was not statistically significant, but which nearly was so. The effect of asking questions was marginally significant upon the probability of a response being associated with the *All moderate* profile ($\beta = 0.023$ (0.017), $p = .090$; *partial* $R\hat{}2 = .001$).

Table 4.5: Results of mixed effects models with the interactions between interest and other characactistics and the composite for work with data

Profile	Universally low	Only behavioral	Only affective	All moderate	Eng. and comp. but not chall.	Full
Youth characteristics						
Pre-interest	-0.047 (0.022)	-0.013 (0.012)	-0.012 (0.019)	0.039 (0.016)*	0.007 (0.01)	0.018 (0.021)
Gender-Female	0.06 (0.037)	0.019 (0.019)	-0.038 (0.033)	0.025 (0.028)	-0.02 (0.018)	-0.035 (0.037)
URM status	-0.01 (0.052)	0.031 (0.026)	-0.076 (0.046)*	-0.012 (0.04)	0.018 (0.025)	0.043 (0.053)
Aspects of Work With Data						
Asking	-0.015 (0.018)	0.015 (0.015)	0.023 (0.017)*	-0.011 (0.015)	0.004 (0.014)	-0.019 (0.016)
Observing	0.003 (0.018)	0.013 (0.015)	0.007 (0.017)	0.009 (0.015)	-0.017 (0.014)	-0.025 (0.016)*
Generating	-0.014 (0.017)	0.014 (0.014)*	0.012 (0.016)	-0.014 (0.014)	-0.02 (0.013)	0.027 (0.015)*
Modeling	0.004 (0.019)	-0.023 (0.016)	-0.004 (0.018)	0 (0.015)	-0.012 (0.015)*	0.034 (0.017)*
Communicating	0.002 (0.018)	0.018 (0.015)	-0.011 (0.017)	0.004 (0.015)	0.016 (0.014)	-0.027 (0.016)

4.6 Results for Research Question #5: Youth characteristics and engagement

While the section for results for research #4 focused on the rows for the variables for the aspects of work with data, this section focuses on those for the youth characteristics. As for the previous research question, the first row is again associated with the results for the model predicting the probability of the *Only behavioral* profile, with the cells across the columns containing the coefficients, their standard errors, and their p-values; for this question, the youth characteristics are interpreted.

In terms of youths' pre-program interest, these analyses show that youth who enter the program with higher levels of interest (in STEM) are more likely to report being in the *Engaged and competent but not challenged* profile (β = 0.039, p = .009; *partial R^2* = .001). In other words, youth who are more interested at the outset of the program report working harder, learning more, enjoying themselves more, and feeling more competent when they are actually involved in a program activities, though they also report lower levels of challenge. For this effect, 17.879% would be needed to invalidate the inference, a slightly larger value for the follow-up sensitivity analysis than those found for the (statistically significant) relations involving the aspects of work with data, suggesting a moderately robust effect.

Female youth reported more often than males that they were in the *Universally low* profile, though this difference did not quite reach statistical significance (β = 0.037, p = .051; *partial R^2* = .006). The effect size again suggest very small effects in substantive terms. For this effect, 17.843% of the bias would need to be removed (or the effect would need to be larger by this percentage) to sustain the inference. The moderately large amount of bias that would need to be removed for the effect of being female (on the *Universally low* profile) to be significant suggests that this effect should not be very seriously interpreted.

There were not any statistically significant effects of youths' URM status. This may be a function of the large proportion of youth from under-represented (in STEM) racial and ethnic groups: hispanic (48%), African American or Black (36%), and youth who identify as being from multiple racial and ethnic groups (3%) made up 87% of the youth in the programs, so there were not many youth who were *not* from under-represented groups in the sample, suggesting that the absence of findings may be due to this small sample (and low statistical power). Nevertheless, no relations between URM status and youths' engagement were found, indicating that there is at least not evidence that youth from such backgrounds do engage in different ways.

These (somewhat minimal) findings for the youth characteristics were more surprising than those observed for the aspects of work with data. The results of research question #3, on the sources of variability for the profiles of engagement, suggested that there was a lot of systematic variability at the level of the youth (there were large ICCs at the youth level, with smaller ICCs at the instructional episode level). Because pre-interest, gender, and URM status are variables at this level, it could be expected that they would have important relations with the profiles of engagement. However it appears that the particular youth characteristics considered were not effective at explaining much of this variability; possible reasons why are discussed further in the next section.

Chapter 5

Discussion

5.1 Key Findings

5.1.1 Key findings for the frequency and nature of work with data

These findings provide some of the the first information (that I am aware of) for how frequent work with data is in summer STEM programs. In addition, the findings shed light on the specific, qualitative nature of work with data in these contexts. As I mention, these findings have implications for how science is taught, both in similar, outside-of-school settings and some value in terms of speaking to the role of work with data during formal, K-12 education settings. In the context of describing these findings, I also highlight how the use of video-recordings of the STEM programs was necessary for being able to make claims about the frequency and nature of work with data during them.

In terms of the frequency of work with data, work with data was found to be common in the summer STEM programs: 170 out of the 236 instructional episodes contained at least one of the five aspects (asking questions, making observations, generating data, data modeling, and interpreting and communicating findings) of work with data. The use of video-recordings of the programs and the strategy of using ESM to select (mostly) random samples of youths' experiences during the programs enabled me to show just how frequent work with data was, and I found that specific aspects of work with data were more or less frequent: Making observations, in some form, occurred during 24% of the program's time, while generating data and communicating findings both occurred during 43% of the instructional episodes. Data modeling, like making observations, was somewhat less frequent (29%), whereas asking questions and generating data, like communicating findings, were relatively more common (38%).

Given the design and goals of summer STEM programs, these align with what may be expected given past research: Such programs are designed to engage youth in the practices, including and as I argue earlier *especially* those relating to work with data, of STEM domains (Dabney et al., 2012; Elam et al., 2012). Even still, these are the first results of this kind that I am aware of (in terms of the proportion of the time spent in the programs). Using video-recording data and a sampling strategy that can provide insight into the amount of overall time spent was an important component of achieving these findings. While there are not other results of this particular kind, a related, an area of related work concerns other studies that has used the PQA measure (recall that in the present study the STEM-PQA measure was adapted for examining work with data). However, studies have (yet) used the version that is adapted for STEM content areas. Some reports call for greater use of measures (such as the PQA) in the study (and evaluation) of summer and outside-of-school STEM programs (e.g., Yohalem et al., 2005). As one example of such a study (but one that is not focused on STEM), Smith et al. (2012) reported findings from a continuous improvement intervention (that used a rigorous experimental design), finding that the intervention positively impacted the quality of instruction in the programs.

In-depth qualitative analysis that aimed to show the specific ways work with data was enacted during the programs. This analysis revealed that there was often a variety of ways in which each of the aspects were carried out, with implications for how youth may engage in each of them. Many times, youth engaged in what can be described as ambitious and potentially highly engaging ways of being involved in work with data. When youth were asking questions, they regularly (during 39% of the episodes that involved this particular aspect of work with data) worked to make predictions or hypotheses about the phenomena they were exploring or the problem they were seeking to solve. When making observations, they were often (in 86% of the episodes) did so of phenomena in the field (such as an estuary or an island in the case of science-focused programs) or (in the case of mathematics and engineering-focused programs) workshop or through computers in classroom settings. When generating data, many times (in 47% of the episodes that involved this aspect) youth recorded their own observations; when modeling data, youth were involved (in 72% of the episodes) in the use of statistical and mathematical models of real-world phenomena. When interpreting and communicating findings, youth regularly (during 48% of episodes) had opportunities to share (with other youth in the program) what they found or created as a result of their earlier investigations or work.

Also of note was what occurred during the rest of the time: When youths' questions, for example, were not focused on predicting or hypothesizing about what they were exploring, they type of question was more general, or was instructor-led, rather than driven by youth. Especially for this aspect of work with data (asking questions) as well as when generating data and interpreting and communicating findings, a substantial proportion of the instructional episodes that involved these aspects of work with data were not as ambitious (and not as much in alignment with recent policy documents and curricular standards, i.e. National Research Council, 2012; NGSS Lead States, 2013; National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010). In the scientific and engineering practices in the NGSS and the standards for mathematical practice in the Common Core State Standards), work with data is described by grade-level bands. For instances, in grades 6-8, students are expected to that ask questions, for example, to determine relationships between variables and relationships in models (NGSS Lead States, Appendix F, 2015). It is *not* expected that students engage in all of the aspects of a practice at once. However, as McNeill and Berland (2017) argue, it is not just engaging in these practices by rote, but about integrating them, as they overlap and interconnect.

Also of note was the frequency of these three aspects of work with data overall: They occurred much more frequently than the two (making observations and data modeling) for which a larger proportion of their enactment was more in-line with policy and curricular standards. What this suggests is that while work with data that was ambitious and potentially highly-engaging to youth was found to be common (according to the quantitative analysis), this qualitative analysis showed that there how the aspects of work with data took place varied a lot: The type of activities that may be the most demanding for youth were still common, but not quite as common as the overall frequencies presented for the quantitative would suggest.

While descriptive in nature, these results present the first insight that I am aware of of the extent of work with data in STEM enrichment programs. They suggest that, as past scholarship (National Research Council, 2009, 2012) can provide a context for youth to be involved in the type of scientific and engineering practices-focused activities that can be particularly powerful for youth (and students) in terms of their learning. The use of video-recordings of data was especially helpful in establishing this descriptive data.

The nature of the aspects of work with data in such settings can more easily (than the frequency of the aspects of work with data) be compared to past research. This past research points out the heterogeneity in how work with data is enacted in educational settings. For example, McNeill and Berland (2017). They argue that a view of work with data focused on sense-making with real-world phenomena and iterative cycles of engaging in work with data, and revision of intermediate ideas. In this sense, some of what was observed in the programs aligned with work with data, while others did not.

Another comparison is other studies investigating data modeling. Past research, for example, highlights use of "data to solve real problems and to ask authentic questions" (Hancock et al., 1992, p. 337). Research on generating data emphasized an aspect not very much the focus of the present research, namely, structuring data into spreadsheets (Konold, Finzer, & Kreetong, 2017; Lehrer & Kim, 2009). Research on posing questions that can be answered with data shows that there is a connection between student-centered teaching strategies and students' ability to ask empirical (Bielik & Yarden, 2016). This suggests a reason why youth were able to ask questions and ideas for how they might do so more: Make activities in summer STEM program youth-centered, rather than instructor-centered. Research on the data modeling aspect of work with data highlights the use of statistical models much more than the physical models which were sometimes found to be a way in which youth engaged in data modeling (Petrosino, Lehrer, & Schauble, 2003; Lesh, Middleton, Caylor, & Gupta, 2008; Lee, Angotti, & Tarr, 2010). Nevertheless, many of the ways youth engaged in data modeling aligned with this past research, particularly when the goal of the activity is to model variability. This past research that encouraging youth to consider summaries of data, such as the mean and standard deviation, may be a promising way for them to engage more deeply in data modeling (Lehrer, Kim, & Schauble, 2007; Lehrer & Schauble, 2004). In this way, some (but not all) of the aspects work with data aligned with past research; when they align, they are encouraging, and when they do not, some ideas for how to involve youth in more engaging aspects of work with data are able to be identified.

5.1.2 Key findings for what profiles of engagement were found

These findings provide insight into how youth experience engagement together and at once. By together and at once, I refer to the profile approach used that was used to identify common groups of youths' responses. This approach provides information about youths' engagement that is different from that gained from other approaches.

Six profiles of engagement were found using a rigorous model selection approach. Before discussing these results in-depth, it is important to note that LPA is an exploratory approach: The number and nature of the profiles identified were found through a rigorous and systematic approach, but this is not a guarantee that the same number and make-up of profiles would emerge.

Six is, in the context of these possible caveats, the same exact number of profiles of engagement identified in recent, past research. Schmidt et al. (2018) found six profiles of engagement. Their profiles were constructed on the basis of the indicators (cognitive, behavioral, and affective) of engagement, and not perceptions of challenge and competence. Nevertheless, the similar number provides further information about the nature of engagement in educational contexts. Namely, six is a number of profiles that is larger than the number of profiles identified in other fields (see Wormington and Linnenbrink-Garcia, 2017, for a review in motivational settings). However, as large as six profiles is, it is not a number that is far higher than the average, suggesting that there may be a greater variety of types of engagement exhibited than, for example, types of motivation.

In terms of the make-up of the specific profiles, those found in the present study included those that were strongly negative (*Universally low*) and strongly positive (*Full*), as well as those characterized by different levels of engagement (*Only behavioral* and *Only affective*) and by different levels of the conditions of engagement (Engaged and Competent but not Challenged). An *All moderate* profile was also identified. Little research has examined profiles of engagement, though Schmidt et al. (2018) examined profiles of engagement, constructed from items for cognitive, behavioral, and affective engagement (but not perceptions of challenge and competence), and found six profiles, some of which partially overlap with those found in the present study. In particular, on the basis of the items shared between the studies, a *Universally low*, *All moderate*, and *Full* profile were found in both studies. However, as these profiles are characterized by the (uniform) level across all of the variables, this is only limited evidence for the presence of these profiles in the larger population of youth engaged in science and STEM-related learning activities.

These profiles have implications for the study of engagement and the analysis of multidimensional data on youth and student engagement. First, they suggest that perceptions of challenge and competence be considered in future research. This is because some of the profiles were distinguished on their basis. This approach also may be more parsimonious than including perceptions of challenge and competence as separate predictors (i.e., Shernoff et al., 2003). In addition to these empirical reasons, past research on engagement (i.e., Csikszentmihalyi, 1990) and on the profile approach (Bergman & Magnusson, 1997) suggest that they are theoretically inseparable from engagement, another reason for modeling them as they were modeled in the present study. These implications are specific to the study of engagement but also highlight some of the promise of the profile approach, as well.

5.1.3 Key findings for sources of variability for the profiles

These findings help us to understand how much variability in youths' engagement can be attributed to variables: both those that are measured in this and related studies and those that are not or cannot be measured at different levels, namely youth, instructional episode, and program. What these findings suggest about what relations can be anticipated from predictors at different levels is discussed, as well as how researchers can use null models as used in the present study to understand variability at different levels.

The profiles suggest that the experiences of youth in summer STEM programs are variable and that the use of ESM can aid in the study of youths' engagement. The source of this variation can be due to many different factors, including individual differences between youth, the nature of the instruction carried out, and program-specific factors: Knowing about these sources provide valuable information in their own right, a benefit of the use of mixed effects models (Gelman & Hill, 2007).

The findings for this question were somewhat surprising and disappointing given past research. In particular, youth-level sources of variability were by far the largest, explaining between .093 to .432, depending on the profile: This means that between around 10% and 40% of the unexplained variability in the profiles is attributable to youth characteristics, both those that can be captured with variables and those that are at the youth level but are not measured (or are not measurable but are still at this level). Furthermore, the amount of variability at the instructional episode and program levels was small, no greater than .031 for the instructional episode or .023 for the program. A promise of the use of ESM is that it is able detect contextual differences in youths' experiences: The small amount of variability that can be explained at this level suggests that, for the engagement profiles, not much difference exists from instructional episode to instructional episode.

This finding related to minimal variability at the program and particularly at the instructional episode level is useful in its own right. It also suggests that engagement, as measured in this context with ESM and with the engagement items used, may be more stable than dynamic at the instructional episode level, differing from some past theory (e.g., Skinner & Pitzer, 2012) and research that showed relations between instructional episode-level variables and engagement (e.g., Shernoff et al., 2016; Shumow, Schmidt, & Zaleski, 2013). This also suggests that variables at these levels do not have a substantial proportion of variability to explain: Predictor variables (like those for the aspects of work with data) at the instructional episode level had much less variability to explain, while those at the youth level had a substantial amount that was able to be explained.

One factor of note concerns the analytic approach used. As noted, the profiles demonstrated very little variability at the program and instructional episode level, suggesting that factors at this level would likely not strongly predict the profiles. This could be a function of the use of profiles and the specific variables selected. It may also be the result of the outcome (engagement and its conditions) selected. Other analytic approaches can be carried out to determine the viability of the profiles approach and use of the items for engagement and its conditions for understanding work with data.

While these are important limitations, it is worth noting that the modeling strategy (with the mixed effects models) is inherently a conservative (particularly in terms of the statistical significance of hypothesis tests) approach. Thus, while the findings detected are small, they can be considered to be trustworthy on the basis of the way the ESM data were analyzed. This trustworthiness is enhanced by the use of sensitivity analysis, which showed how much of the effects could be due to bias for them to be invalidated.

5.1.4 Key findings for how work with data relates to engagement

These findings show minimal but important relations between the aspects of work with data and youth engagement. They are discussed in the context of past research on work with data and youth engagement in scientific and engineering practices more generally. Finally, some possible reasons for the minimal findings are brought up.

In line with what the preliminary analysis of the amount of variability that could be explained at the youth, instructional episode, and program levels, relations between work with data were largely not found, though some small, statistically significant relations were identified. These findings, overall, were not necessarily surprising given past research: The question of whether and how work with data relates to engagement has not been the focus of any past research. In this sense, these are important findings that suggest that work with data may not be strongly related to engagement.

Given the small amount of variability at the instructional episode level, this result was anticipated (on this basis). Importantly, however, there were some noteworthy findings. In particular, both generating and modeling data were found to be positively (and statistically significantly) related to the *Full* profile, suggesting that when youth are involved in these practices, then they are more likely to be highly engaged. In particular, given the makeup of this profile, this suggests that when youth are involved in these aspects of work with data, they are more likely to report high levels of cognitive, behavioral, and affective engagement, and high perceptions of competence and challenge. The effect of data modeling was more robust than that for generating data, the latter which should be interpreted with caution. In short, this suggests that these activities are beneficial to youths' engagement.

As there is no research on how work with data relates to youths' engagement, the findings associated with this research question provide some, albeit limited, evidence (and directions for future research) for how some aspects of work with data relate to youths' engagement. As work with data is a core component of new visions for STEM learning (see the scientific and engineering practices that are part of the NGSS and the standards for mathematical practice in the CCSS), these findings provide some insight into how involvement in a subset (focused on work with data) of these practices relates to engagement. Particularly, the relatively minimal findings suggest that these activities may not be more engaging *per se*. Instead, it may be the way that youth engage in them that matters, in alignment with past research (Berland et al., 2017; Miller et al., in press).

While the findings for this question were somewhat minimal, there are key findings from both the important relationships that were found to be statistically significant (between generating data and data modeling and *Full* engagement) and from those that were not. Finding few significant findings may show that, in this sample and with work with data as carried out, it is difficult to say with certainty just how much of an impact work with data has upon youths' engagement. This suggests that other samples, other enactments of work with data, and, possibly, other analytic approaches can build on this work to further substantiate what is known about how work with data is engaging to youth.

5.1.5 Key findings for how youth characteristics relate to engagement

These findings, more surprising given the amount of variability able to be explained by variables at the youth level and the minimal relations, are discussed, followed by some reasons for why there are not more (and stronger) relations.

First, the relations between youth characteristics and the profiles were found to be small and not as much in line with expectations given the preliminary analysis. These small relations were similar (in magnitude) to those between work with data and the profiles, but they were more surprising for a reason related to the sample for this study, namely, given the substantial variability at the youth level among the responses. This is described in detail in the discussion of the findings for research question #3.

Findings for this question revealed that youth with higher pre-program interest were more likely to be *Engaged and competent but not challenged*. This suggests that youth with higher interest in STEM are inclined to be highly engaged and good at what they are doing, but are not challenged by the activities they experience. This finding is in line with past research suggesting a relationship (direct or as a moderator) between youth characteristics (including interest) and their engagement (Shernoff et al., 2003; Shernoff et al., 2016; Strati et al., 2017). More specifically, this finding suggests that for youth who are particularly interested (and those who choose to attend) summer STEM programs, what they are involved in may not challenge them very highly. This finding has implications for past research that shows youth who choose to attend summer STEM programs are more engaged (but that does not speak to their degree of challenge; Beymer, Rosenberg, Schmidt, & Naftzger, 2018).

In terms of youths' gender, the analysis for this question revealed that female youth who are engaged in work with data *may* be (note that this result was not statistically significant) more likely to be fully engaged. While this finding cannot be interpreted on the basis of the results from this study, given that past research has found that female students are less likely to be engaged in STEM classes (e.g., Patall et al., 2017), it suggests that this relationship between gender and youths' engagement be considered further in follow-up studies. At present, we have limited information about what types of instruction may best support female students to be engaged and successful both in summer STEM and other settings.

While the findings for this research question, like those for the relations between the aspects of work with data and youths' engagement, they provide some information about how these characteristics relate to youths' engagement. Finding that youth who are more interested prior to the beginning of the summer STEM programs are more likely to be working hard, learning something new, and enjoying what they are learning, and perceive themselves to be good at what they are doing but not challenged, is a meaningful finding. Moreover, the null findings suggest that other characteristics, including those measured but not included for this analysis (such as youths' pre-program perceptions of their competence) as well as those not measured at all, may be considered in follow-up studies and in future research.

5.2 Limitations of the Study and Recommendations for Future Research

This study examines youths' engagement as an outcome. Accordingly, outcomes from engaging, such as the products of neither youths' work or the specific cognitive capabilities they develop through their participation, are not the focus. Thus, while some findings about how work with data and youth characteristics were found to be associated with different profiles of engagement, we do not have an understanding of how engaging in more or less adaptive ways relates to these outcomes. Examining how work with data and engagement relate to key learning, motivational, and future goals and plans-related outcomes is a topic for future research.

Another limitation concerns the context of the study, summer STEM programs. While the programs that were involved in the study have many affordances for work with data and for being highly engaging for youth, they have some limitations, too, particularly with respect to support work with data. Importantly, these were not programs explicitly designed to support work with data; while such contexts are being developed, they are not yet widespread. Learning environments that deliberately support work with data over a long period may demonstrate different patterns of engagement than those examined in this study because of the focus on and sequencing of the aspects of work with data, which may make it more (or less) cognitively, behaviorally, or affectively engaging than is determined in this study. As Miller et al. (2018) highlight, truly engaging STEM activities are not easily come by; they require students to take ownership over and to make decisions about their explorations or designs. Thus, future research may study work with data in contexts designed to support it. A key part of this future research may be studying both work with data and how work with data is supported (most importantly by the instructor but also by the curriculum and technological tools).

A related limitation is that the programs that were the focus of this study were model programs, or those based on characteristics of exemplary STEM enrichment programs. As a result, engagement may be different in other STEM enrichment programs depending on characteristics of the programs and their activities, and findings from this study should be interpreted in terms of programs that share similar characteristics.

It is possible that the somewhat minimal findings are, in part, a result of the analytic approach. A similar mixed effects modeling approach has only been used in one other study (Strati et al., 2017), and that approach did not use profiles (as in this study) as the outcome. In this study, little variability at the instructional episode level was found, and so minimal relations between factors at this (instructional episode) level and the profiles of engagement was expected. Might profiles, but not the variables used to create them, be less variable at the instructional episode level? One way to consider such an alternate explanation is to use the data used in this study as part of a correlational analysis, or another analysis that uses that variables used to create profiles of engagement but does not use the profiles themselves.

A final limitation concerns the measures used for work with data. The dimensions of the STEM-PQA measure aligned closely with the aspects of work with data. But, there were some possible divergences that may have had an impact upon some of the findings. For example, for the interpreting and communicating findings code, the STEM-PQA codes for *Analyze* ("Staff support youth in analyzing data to draw conclusions") and *Use symbols or models* ("Staff support youth in conveying STEM concepts through symbols, models, or other nonverbal language") were used. In the case of the latter STEM-PQA code, conveying STEM concepts through symbols, models, or other nonverbal language could have reflected instructional episodes in which youth used, for example, mathematical equations or formulas, but did not do so as part of modeling data of a phenomena in the world: They could have simply been using an equation outside of the context of any particular phenomena. Future research may consider use of coding for this aspect of work with data (and this aspect of science curricular standards in particular; see NGSS Lead States, 2013).

As another example of this limitation, generating data was an aspect of work with data that the open-ended qualitative analysis revealed to be less associated with less systematic groups of practices, or themes, than the other aspects. The STEM-PQA codes corresponding to this aspect of work with data were *Collect data or measure* ("Staff support youth in collecting data or measuring") and *Highlight precision and accuracy* ("Staff highlight value of precision and accuracy in measuring, observing, recording, or calculating"). Particularly in the case of the latter code, the emphasis on precision and accuracy may have been outside of activities focused on recording data or creating coding frames. Future research may consider a coding frame that is (even more) focused on generating data, though considerations of precision and accuracy are key aspects of doing so, and so perhaps separating the act of generating data from considerations that are important to keep in mind while doing it may be a promising direction for future research.

While these divergences in measures were not large, they suggest that the coding frame for work with data is a limitation of the present study. McNeill and Berland (2017) describe a similar type of disagreement across science education settings: While a limitation, the coding frame did represent agreement across a range of studies across STEM contexts for the aspects of work with data, although I recognize that this coding frame may not distinguish the different ways in which work with data is enacted, as revealed by the qualitative coding carried out in this study.

5.3 Implications for Practice

Two key implications related to engaging youth in generating and modeling data and including other practices to the extent that they involve youth in generating and modeling are discussed. While this is somewhat limited evidence, this study suggests that *generating data* and *modeling data* in particular may be beneficial in terms of engaging youth. Generating data in particular may be a key practice because it involves making work with data concrete; as Lehrer and Schauble (2015) describe, recording data in the form of "inscriptions" can serve as commitments that youth make (in terms of what data were chosen to be collected and recorded). This implication, in particular, should be interpreted with caution, however, given the very small magnitude of the effect. Similarly, data modeling has been described as *the* central scientific and engineering practice (Schwarz et al., 2009; Lehrer & Schauble, 2015; Weisberg, 2012), and its relations with full engagement provides some actionable evidence for its importance in the context of summer STEM programs.

Practically, youth activity leaders (in summer STEM and other STEM enrichment contexts) and teachers (in formal learning environments) can best include the beneficial practices of generating and modeling data not in isolation, but rather through involving youth and learners in complete cycles of investigation. This aligns with both foundational and contemporary research on work with data in education (Berland et al., 2018; McNeill & Berland, 2017; Hancock et al., 1992; Lee & Wilkerson, 2018). Recent curricular reform efforts also suggest that the best way to engage learners in particular practices is through the process of identifying a question or problem, marshaling sources of data that can be used to figure out what is happening, and developing model-based explanations that are then communicated (or even used in an argument; National Governors Association, 2013; National Research Council, 2012; NGSS Lead States, 2013). With respect to work with data in particular, youth activity leaders and teachers can use the findings from this study as a starting point to consider how engaging in work with data may also prepare learners to think of, understand, and take action based on data in their day-to-day lives. Many questions or problems learners face may involve data that can be meaningfully incorporated into engaging learning activities.

5.4 Implications for the development of open source tool

A final note concerns how the modeling was carried out. Because LPA is an exploratory approach, it requires a blend of exploring the data while also systematically taking account of how the solutions change while different solutions are explored. Because of the challenge of doing this, I developed an open-source tool that made it easier to work toward the aim of systematically exploring the data. Other educational researchers may consider the utility of such development efforts, though such efforts are not a regular part of the products created in the course of most educational research. Such development work by educational researchers may even inform the type of activities youth do when working with data: While a STEM content area, programming and computer science-related activities were not emphasized as much as those related to science, mathematics, and engineering.

5.5 Conclusion

Each of the disciplines that contribute to STEM learning involve work with data and how youth and students work with data in engaging ways is a concern of researchers and practitioners. While past research has focused on what aspects of work with data learners are involved in with respect to work with data, or specific conceptual outcomes from working with data, little research has considered youths' experience of working with data. In this study, engagement was used as a lens to understand the experience of youth working with data in the context of nine summer STEM programs. In particular, five aspects of work with data, a) asking questions, b) observing phenomena, c) constructing measures and generating data, d) data modeling, and e) interpreting and communicating findings, were identified from video-recordings of the programs. These codes were then used to predict profiles, or distinct groups on the basis of different levels, of youths' cognitive, behavioral, and affective engagement, and two other variables, youths' perceptions of challenge and competence. These measures were obtained using an innovative method, ESM, that provides some access to youths' experience in-the-moment of the activities they were involved in during the program.

Findings indicate that work with data occurs regularly in the programs and that there are some examples of ambitious activities centered on working with real-world data (and examples in which the work with data is not fully aligned with youth-driven work with data). Six profiles of engagement were identified, representing different configurations of engagement. Relations of work with data and youth characteristics (pre-program interest in STEM and youths' gender and status in terms of being a member of under-represented groups in STEM) were, overall, not strongly related with the profiles of engagement, though some key findings were identified. Generating and modeling data were both related to the most potentially beneficial profile, one characterized by high levels of all five of the variables used to create the profiles. Female youth who were involved in work with data (at the instructional episode level) to a greater extent were also more likely to be fully engaged. This study suggests that work with data has purchase as an organizing set of activities for STEM can have some benefits in terms of understanding the nature of what youth do in summer STEM programs. In addition, this study shows that ESM and engagement can be used to understand youths' experiences. Data–and who is able to work with data–have important roles in STEM learning and in society; efforts to understand and support learners engaging in these ambitious activities should be encouraged and expanded.

Chapter 6

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Chapter 7

Appendix

7.1 Appendix A: STEM-PQA alignment

Table 7.1: Alignment of codes for instructional support for work with data and the STEM-PQA

Work.With.Data	Description	STEM.PQA
Asking questions or defining problems	Discussing and exploring topics to investigate and pose questions.	Predict, conjecture, or hypothesize
Making observations	Watching and noticing what is happening with respect to the phenomena or problem being investigated.	Classify or abstract
Generating data	Figuring out how or why to inscribe an observation as data and generating coding frames or measurement tools.	Collect data or measure; Highlight precision and accuracy
Data modeling	Understanding and explaining phenomena using models of the data that account for variability or uncertainty.	Simulate, experiment, or model
Interpreting and communicating findings	Discussing and sharing and presenting findings.	Analyze; Use symbols or models

7.1.1 Appendix B: Program descriptions

Table 7.2: Program (with pseudonyms) descriptions

Program.Name	Program.Description
Island Explorers	A science-focused program that aims to help youth develop expertise on one species found in the local ecosystem by reading and writing about related content for up to an hour per day; undertaking data collection and analysis tasks to learn about the local ecosystem and how to communicate scientific data; developing vocabulary about the local ecosystem; using art to learn and communicate information; and publishing a book illustrating important elements of the species being studied. Located in both the classroom and local ecosystem. 27 students who are rising 6th graders. Youth spend the morning in more academically-oriented sessions in a classroom setting, while afternoon sessions involved STEM-oriented enrichment sessions taking place outside (the program was associated with Outward Bound) with an emphasis on exploration of the local ecosystem.
The Ecosphere	A science-focused program that aims to help youth to explore the marine life of Narragansett Bay. Efforts were undertaken to build youth content knowledge in the areas of ecosystem preservation, marine biology, and water quality, and related skills, such as questioning, showing initiative, data collection, measuring, maintaining an ecosystem, and analyzing water samples. Located in a classroom setting, shoreline, and science education center. 27 youth who are rising 6th to 9th graders. Youth attended programming in a classroom at an area middle school and in a field-based setting on alternating days. Field-based settings included a science education center at a community-based organization and field trips to sites in the community related to the program's focus.
Zoology Partners	A science-focused program that aims to support youth's development of content knowledge related to the issue of endangered species, including how species become endangered, processes for monitoring ecosystem viability and population levels, solutions to prevent species from becoming endangered, and approaches to reviving populations that are currently endangered. Located in the classroom as well as zoos, parks, and other natural areas. 25 youth who are rising 6th to 9th graders. Youth attended programming in a classroom at an area middle school and in a field-based setting on alternating days. Field-based settings included a local zoo and field trips to sites in the community related to the program's focus.
Marine Investigators	A science-focused program that aims to provide youth with opportunities to learn about and experience Narragansett Bay; examine human impacts on the local ecosystem, including how the geography of the Bay helped influence human history and how the history of humans along the shoreline has impacted the Bay, and begin the process of cultivating a sense of stewardship among participating youth for caring for and protecting the Bay in the future. Located in the classroom, shoreline along the bay, ship on the bay, and various field locations associated with bay health. 19 youth who are rising 7th to 9th graders. Youth attended programming in a classroom at an area middle school and in a field-based setting on alternating days. Field-based settings included the local bay shoreline, a voyage on a marine education ship researching in the Bay, and field trips to sites in the community related to the program's focus. During the span of the program, youth had the opportunity to participate in both a water quality research study.
Comunidad de Aprendizaje	A STEM-focused program that aims to help youth improve basic skills in mathematics and develop an interest in STEM content and entrepreneurship. Primarily in the classroom setting. 33 students who are rising 5th to 8th graders. Morning sessions are characterized by direct instruction in mathematics for individual grade levels and mixed grade level afternoon enrichment sessions in either robotics or dance. The direct instruction component of the programs was organized around a theme of promoting entrepreneurship with the goal of helping participating youth better see the relevance of mathematics to future career goals and opportunities.
Jefferson House	A STEM-focused program that aims to support youth's development of basic math skills, the program was primarily focused on helping youth develop problem solving, self-improvement, and critical thinking skills. Located in a classroom. 11 youth who are rising 7th graders. The youth spent the morning in more academically-oriented sessions in a classroom setting focusing on basic skill development, while afternoon sessions involved STEM-oriented enrichment sessions involving media, art, and nutrition. Enrichment offerings varied by day, with math sessions occurring twice per week, alternating with academically oriented sessions in the am that were oriented at supporting skill development in English/language arts.
Uptown Architecture	An engineering-focused program that aims to support youth's participation in a process to design and build an outdoor learning space for use at the middle school where the program was housed. A key focus of the program was to provide youth with the opportunity to use design thinking as a problem-solving tool and have the experience of affecting their community positively through the design/build process. Located in a classroom, building shop, and various field locations. 18 youth who were rising 6th to 9th graders. Youth attended programming in a classroom at an area middle school and in a building shop located at a community-based organization on alternating days, while also taking field trips to locations associated with the program's overall theme.
Building Mania	An engineering-focused program that aims to provide youth with the opportunity to experiment with designing and using simple machines. A goal of the program is to have youth engage in the engineering design process by determining a need, brainstorming possible designs, selecting a design, planning and drawing out the design, creating and testing and revising it, and producing a final machine. Located in the classroom, design labs, and other local locations. 24 youth who are rising 6th to 9th graders. Youth attended programming in a classroom at an area middle school and a field-based setting on alternating days. Field-based settings included a design lab at a community-based organization and field trips to sites in the community related to the program's focus.
Adventures in Mathematics	A mathematics-focused program that aims to help youth to develop the basic math skills and prevent summer learning loss among participating youth through direct instruction and participation in math-related games. Located primarily in the classroom. 20 youth who are rising 8th to 10th graders. Youth participated in direct instructions in mathematics and math-related games in small groups. Program content was aligned with the state's standards in mathematics.

Table 7.3: Proportion of instructional episodes for which each of the aspects of work with data was present

Aspect of Work With Data	Proportion	N
Asking Questions	0.389	92
Making Observations	0.258	61
Generating Data	0.453	107
Data Modeling	0.288	68
Communicating Findings	0.470	111

7.1.2 Appendix C: Work with data by program

Table 7.4: Proportion of instructional episodes for which each of the aspects of work with data was present by program

Variable	Asking	Observing	Generating	Modeling	Communicating	Total Segments
Island Explorers	0.312	0.375	0.438	0.250	0.375	16
The Ecosphere	0.625	0.417	0.500	0.292	0.500	24
Zoology Partners	0.250	0.167	0.125	0.167	0.208	24
Marine Investigators	0.458	0.333	0.250	0.375	0.542	24
Comunidad de Aprendizaje	0.327	0.182	0.400	0.273	0.327	55
Jefferson House	0.167	0.083	0.542	0.458	0.750	24
Uptown Architecture	0.375	0.208	0.708	0.167	0.292	24
Building Mania	0.333	0.208	0.375	0.333	0.500	24
Adventures in Mathematics	0.583	0.292	0.542	0.458	0.750	24

Note. The *Comunidad de Aprendizaje* program had different sections in the morning and afternoon, which is why the number of instructional episodes is higher than in the other programs.

7.1.3 Appendix D: Model specifications details

Here, the six models that are possible to specify in LPA are described in terms of how the variables used to create the profiles are estimated. Note that p represents different profiles and each parameterization is represented by a 4 x 4 covariance matrix and therefore would represent the parameterization for a four-profile solution. In all of the models, the means are estimated freely in the different profiles. Imagine that each row and column represents a different variable, i.e., the first row (and column) represents broad interest, the second enjoyment, the third self-efficacy, and the fourth another variable, i.e., future goals and plans. Models 1 and 3 meet the assumption of independence, that is, that, after accounting for their relations with the profile, the variables used to estimate the profiles are independent (Collins & Lanza, 2010). They estimate variable variances but do not estimate covariances (i.e., as can be seen, the covariance matrices are "diagonal," without any off-diagonal parameters that are estimated). These models are estimated by default in MPlus, although these assumptions can be relaxed (Muthen & Muthen, 2017). Importantly, this does not mean the variables used to create the profile are assumed to be not related; as Collins and Lanza (2010) explain:

> The local independence assumption refers only to conditioning on the latent variable. It does not imply that in a data set that is to be analyzed, the observed variables are independent. In fact, it is the relations among the observed variables that are explained by the latent classes. An observed data set is a mixture of all the latent classes. Independence is assumed to hold only within each latent class, which is why it is called "local".

Despite the assumption of independence, as Collins and Lanza (2010), Muthen and Muthen (2017), and others (i.e., Pastor et al., 2007; Vermunt & Magidson, 2002) note, it can be lifted to improve model fit, though these models without the assumption of independence may be better described as general or Gaussian mixture models (Fraley et al., 2017).

7.1.3.1 Varying means, equal variances, and covariances fixed to 0 (model 1)

In this model, which corresponds to the mclust model wit the name "EEI", the variances are estimated to be equal across profiles, indicated by the absence of a p subscript for any of the diagonal elements of the matrix. The covariances are constrained to be zero, as indicated by the 0's between every combination of the variables. Thus, this model is highly constrained but also parsimonious: the profiles are estimated in such a way that the variables' variances are identical for each of the profiles, and the relationships between the variables are not estimated. In this way, less degrees of freedom are taken used to explain the observations that make up the data. However, estimating more parameters–as in the other models–may better explain the data, justifying the addition in complexity that their addition involves (and their reduction in degrees of freedom).

$$\begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix}$$

7.1.3.2 Varying means, equal variances, and equal covariances (model 2)

This model corresponds to the mclust model "EEE". In this model, the variances are still constrained to be the same across the profiles, although now the covariances are estimated (but like the variances, are constrained to be the same across profiles). Thus, this model is the first to estimate the covariance (or correlations) of the variables used to create the profiles, thus adding more information that can be used to better understand the characteristics of the profiles (and, potentially, better explain the data).

$$\begin{bmatrix} \sigma_1^2 & \sigma_{21} & \sigma_{31} & \sigma_{41} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} & \sigma_{24} \\ \sigma_{13} & \sigma_{12} & \sigma_3^2 & \sigma_{33} \\ \sigma_{14} & \sigma_{12} & \sigma_{12} & \sigma_4^2 \end{bmatrix}$$

7.1.3.3 Varying means, varying variances, and covariances fixed to 0 (model 3)

This model corresponds to the mclust model "VVI" and allows for the variances to be freely estimated across profiles. The covariances are constrained to zero. Thus, it is more flexible (and less parsimonious) than model 1, but in terms of the covariances, is more constrained than model 2.

$$\begin{bmatrix} \sigma_{1p}^2 & 0 & 0 & 0 \\ 0 & \sigma_{2p}^2 & 0 & 0 \\ 0 & 0 & \sigma_{3p}^2 & 0 \\ 0 & 0 & 0 & \sigma_{4p}^2 \end{bmatrix}$$

7.1.3.4 Varying means, varying variances, and equal covariances (model 4)

This model, which specifies for the variances to be freely estimated across the profiles and for the covariances to be estimated to be equal across profiles, extends model 3. Unfortunately, this model cannot be specified with mclust, though it can be with MPlus; this model *can* be used with the functions to interface to MPlus described below.

$$\begin{bmatrix} \sigma_{1p}^2 & \sigma_{21} & \sigma_{31} & \sigma_{41} \\ \sigma_{12} & \sigma_{2p}^2 & \sigma_{23} & \sigma_{24} \\ \sigma_{13} & \sigma_{12} & \sigma_{3p}^2 & \sigma_{33} \\ \sigma_{14} & \sigma_{12} & \sigma_{12} & \sigma_{4p}^2 \end{bmatrix}$$

7.1.3.5 Varying means, equal variances, and varying covariances (model 5)

This model specifies the variances to be equal across the profiles, but allows the covariances to be freely estimated across the profiles. Like model 4, this model cannot be specified with mclust, though it can be with MPlus. Again, this model *can* be used with the functions to interface to MPlus described below.

$$\begin{bmatrix} \sigma_1^2 & \sigma_{21p} & \sigma_{31p} & \sigma_{41p} \\ \sigma_{12p} & \sigma_2^2 & \sigma_{23p} & \sigma_{24p} \\ \sigma_{13p} & \sigma_{12p} & \sigma_3^2 & \sigma_{33p} \\ \sigma_{14p} & \sigma_{12p} & \sigma_{12p} & \sigma_4^2 \end{bmatrix}$$

7.1.3.6 Varying means, varying variances, and varying covariances (model 6)

This model corresponds to the mclust model "VVV". It allows the variances and the covariances to be freely estimated across profiles. Thus, it is the most complex model, with the potential to allow for understanding many aspects of the variables that are used to estimate the profiles and how they are related. However, it is less parsimonious than all of the other models, and the added parameters should be considered in light of how preferred this model is relative to those with more simple specifications.

$$\begin{bmatrix} \sigma_{1p}^2 & \sigma_{21p} & \sigma_{31p} & \sigma_{41p} \\ \sigma_{12p} & \sigma_{2p}^2 & \sigma_{23p} & \sigma_{24p} \\ \sigma_{13p} & \sigma_{12p} & \sigma_{3p}^2 & \sigma_{33p} \\ \sigma_{14p} & \sigma_{12p} & \sigma_{12p} & \sigma_{4p}^2 \end{bmatrix}$$

7.1.4 Appendix E: Additional details on the model selection process

Looking across the statistics presented, some general ideas about which models are to be preferred emerge. Solutions are interpreted first for each model individually and then across models with the goal of choosing a smaller number of models to investigate in more detail.

Table 7.5: Solutions for models that converged with replicated LL

Number of Profiles	LL	AIC	BIC	SABIC	CAIC	Entropy	VLMR	LMR	BLRT
Model 1									
2	-19894.14	-19894.14	39916.16	39865.32	39820.47	0.807	3468.199 (0)	3397.353 (0)	3468.199 (0)
3	-19453.38	-19453.38	39082.59	39012.69	38951.11	0.794	881.519 (0.0126)	863.512 (0.0136)	881.519 (0)
4	-19196.33	-19196.33	38616.44	38527.47	38449.21	0.811	514.107 (0)	503.605 (0)	514.107 (0)
5	-18817.93	-18817.93	37907.60	37799.57	37704.68	0.913	756.788 (0)	741.329 (0)	756.788 (0)
6	-18648.78	-18648.78	37617.26	37490.17	37378.70	0.888	338.296 (0)	331.386 (0)	338.296 (0)
7	-18407.23	-18407.23	37182.11	37035.95	36907.95	0.886	523.141 (0.0112)	512.455 (0.0121)	523.141 (0)
9	-18186.35	-18186.35	36836.25	36651.96	36491.06	0.899	171.674 (0.1322)	168.167 (0.1359)	171.674 (0)
Model 2									
2	-19107.73	-19107.73	38423.27	38340.65	38267.95	0.924	850.304 (0)	832.934 (0)	850.304 (0)
3	-18897.06	-18897.06	38049.88	37948.20	37858.85	0.880	421.343 (0)	412.736 (0)	421.343 (0)
4	-18659.68	-18659.68	37623.06	37502.32	37396.37	0.922	474.773 (0)	465.075 (0)	474.773 (0)
5	-18474.83	-18474.83	37301.33	37161.52	37039.03	0.901	304.938 (0)	298.709 (0)	304.938 (0)

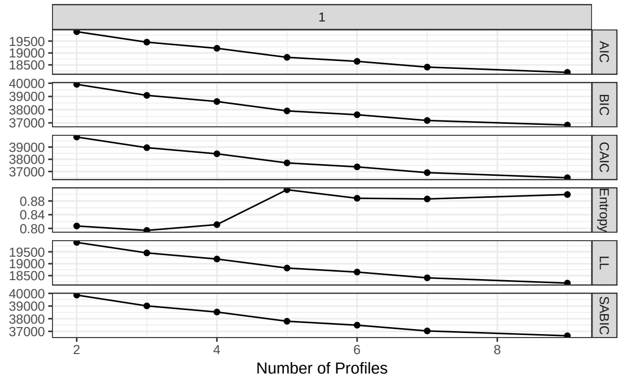


Figure 7.1: Fit statistics for model 1 solutions

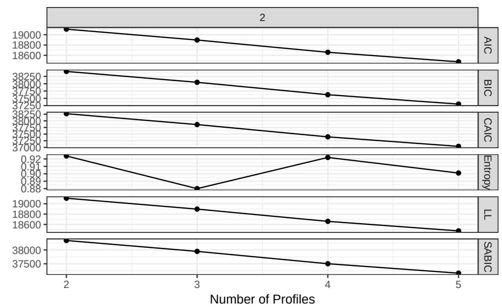


Figure 7.2: Fit statistics for model 2 solutions

For solutions associated with model 1, the decrease (indicating a preferred model) in information criteria becomes smaller as the number of profiles increases from 5 to 6 and 6 to 7. A solution associated with 8 profiles did not replicate the log-likelihood and the VLMR and LMR suggest that the solution associated with 9 profiles did not fit better than that with 8 profiles, suggesting that models with 7 or fewer profiles be preferred. Considering these models, the entropy statistic increases by a large amount between the solution associated with 4 and 5 profiles (and then decreases slightly between 5 and 6 and 6 and 7 profile solutions), suggesting (but not providing conclusive evidence) that models 5, 6, or 7 may be preferred. The bootstrapped LRT suggests that, until the log-likelihood is not replicated, every more complex model be selected. Taking these pieces of evidence into conclusion, for model 1, solutions associated with 4 through 7 may be considered in more depth, with an emphasis on solutions associated with profiles with 5 and 6 profiles on the basis of the slowing of the decrease in the information criteria associated with the solutions with greater profiles than these, and the increase in the entropy from 4 to 5 (and 6) profile solutions.

For solutions associated with model 2, only those associated with 2-5 profile solutions were associated with log-likelihoods that were replicated. For these four models, the log-likelihood decreased in a mostly consistent way, such that changes in the decrease are not as evident as those associated with model 1. The entropy statistic decreases from 2 to 3 profile solutions, increases from 3 to 4 profile solutions, and then decreases slightly from 4 to 5 profile solutions, providing some information that models associated with 4 profiles be preferred to the others. All of the LRTs suggest that the more complex model be selected, not providing clear information about which solutions are to be preferred. On the basis of these pieces of evidence, models with 3, 4, and 5 solutions may be considered in more depth. However, there is a lack of consistent evidence favoring more or less complex models.

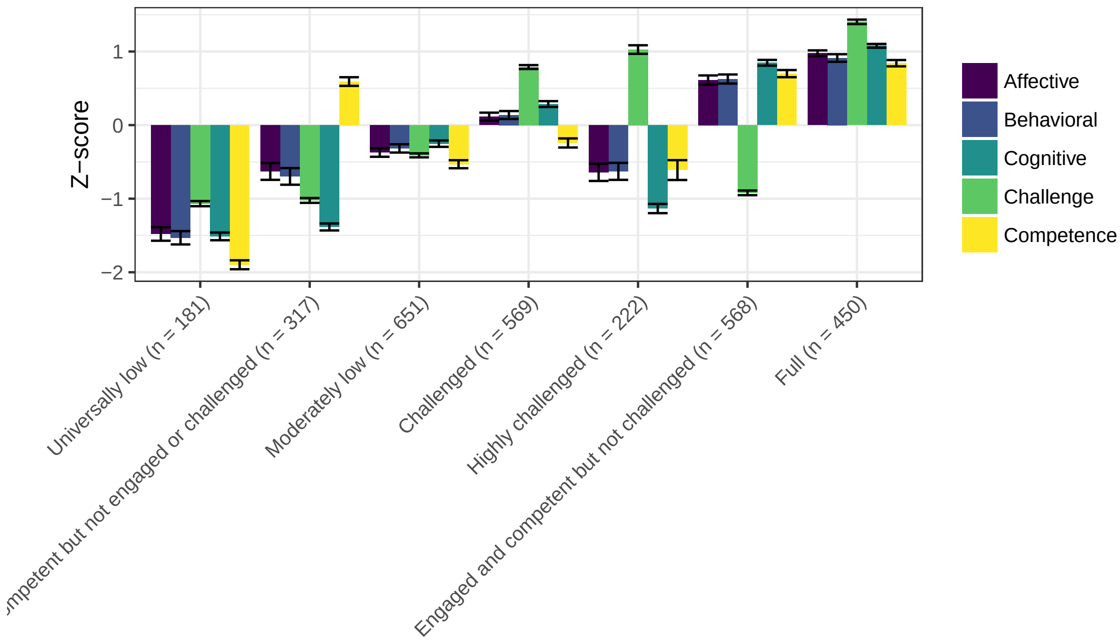
The model 1, six and seven profile solutions are compelling because both show profiles that are distinguished by dimensions of engagement and its conditions (challenge and competence). Note that for this model, only the means and variances are estimated (and so no covariances are estimated), and the variances are constrained to be the same across the profiles. While this is a very restrictive model, it, along with the model 3 type (which did not lead to solutions for any of the numbers of profiles specified) also is a standard model for LPA, in that it meets the assumption of local independence (of the variables that make up the profiles–unlike for models in which covariances are estimated) typical common to LPA (see Muthen & Muthen, 2016). While some of the solutions associated with the model 2 type did reach solutions, these demonstrated less appealing properties in terms of their fit statistics as well as their interpretability and with respect to concerns of parsimony. Thus, while no covariances are estimated for the model 1 type solutions, there is no requirement that these be specified; their benefit, when models associated with them are preferred, is that they can provide better fit: they can be used to better explain or predict the data in a sample, but their inclusion also means that over-fitting the model to the data can become a greater concern.

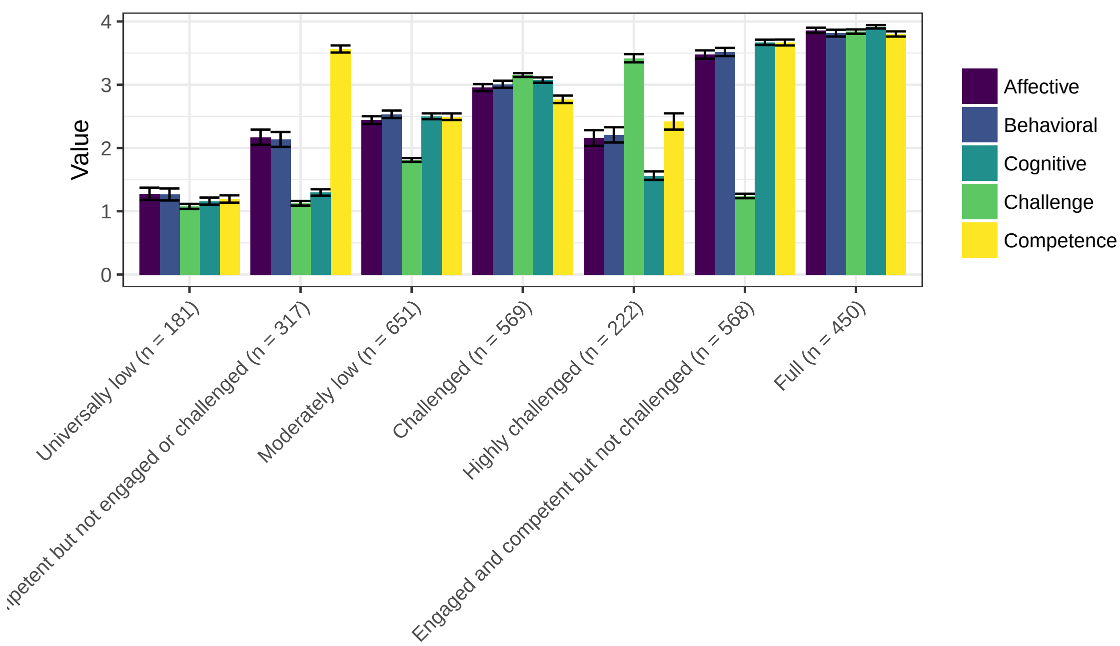
For each solution, alternate solutions associated with higher log-likelihoods were explored. One advantage of the six profile solution is that most of its profiles can also be identified in solutions with fewer profiles. For the six profile solutions, this alternate solution was very different, whereas for the seven profile solutions, this alternate solution was highly similar. The model solutions exhibit a less clear pattern in terms of which profiles appear when. All else being equal, on the basis of parsimony, the model 1, six profile solution is preferred and was selected for use in subsequent analyses.

7.1.5 Appendix F: Alternate model selected (model type 1, seven profile solution)

This solution is characterized by:

- A *full* profile, profile 7
- A *universally low* profile, profile 1
- A *competent but not engaged or challenged* profile, profile 2, characterized by high competence and moderate (low) or low levels of engagement and challenge
- A *moderately low* profile, profile 3, characterized by moderately low levels of all of the variables
- A *challenged* profile, profile 4, characterized by high challenge, moderate (high) levels of engagement, and moderate (low) levels of competence
- A *highly challenged* profile, profile 5, characterized by patterns similar to those of the challenged profile, but with higher challenge and with low levels of both engagement and challenge
- A *challenged but not engaged or competent* profile, profile 6, characterized by low levels of challenge, and high levels of engagement and competence





The number of observations associated with each of the profiles is not very balanced, with few ($n = 181$) observations associated with the universally low profile and few ($n = 222$) observations associated with the highly challenged profile. The number of observations associated with the other profiles ranged from 317 to 651. Distinct from other solutions, none of the other five profiles were found in the other model 1 solutions. Two pairs of the profiles–challenged and highly challenged and universally low and moderately low–exhibited similar patterns among the variables that were distinguished by different mean levels. The log-likelihood was replicated twice, with the next lowest log-likelihood being replicate four times, possibly warranting further investigation. Taken together, this solution raises questions about whether it may be too complex, possibly suggesting preference for model 1 five and six profile solutions.