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

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Chapter 1

Introduction

Changes in how we plan our day-to-day lives, communicate, and learn are increasingly impacted by data. These sources of data are created by us, for us, and about us, although at present opportunities for learners to analyze data in educational settings remain limited. Data analysis includes processes of collecting, creating, modeling data, and asking questions that may be answered with data and making sense of findings. Analyzing data in educational settings, then, is more than just crunching numbers or interpreting a figure created by someone else, but rather is about making sense of phenomena and problem solving (Wild & Pfannkuch, 1999). Data analysis and its processes cut across STEM domains and are recognized as core competencies in both the Next Generation Science Standards and the Common Core State Standards (National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010; NGSS Lead States, 2013). Scholars have pointed out the benefits of analyzing data for learners as young as two years old (Gopnik, & Sobel, 2000).

In supporting teachers and learners' data analysis efforts, some scholars have focused on the process of key data analytic practices, particularly the practices of generating measures of phenomena and creating data models—as an organizing activity in science and mathematics content areas (English, 2012; Lehrer & Romberg, 1996; Lesh, Middleton, Caylor, & Gupta, 2008). Findings from this area of research suggest that engaging in these practices "has an exceptionally high payoff in terms of students' scientific reasoning" (Lehrer & Schauble, 2015, p. 696) and can highlight the utility of mathematics for students' lives (Lesh, Middleton, Caylor, & Gupta, 2008).

While scholars have looked at cognitive outcomes and learners' capability to participate in specific, key aspects of data analysis as well as strategies to address key challenges of doing so, we have not yet examined key data analytic practices in terms of engagement theory. Contemporary engagement theory offers a framework with which to understand learners' experience of engaging in these practices, referred to as work with data in the remainder of this study because it considers multiple dimensions of experiencing engagement and its dynamic nature (Fredricks & McColskey, 2012). Scholars commonly consider engagement in terms of its cognitive (i.e., use of meta-cognitive learning strategies), behavioral (hard work on a task), and affective dimensions (enjoyment; Fredricks, Blumenfeld, & Paris, 2004; Sinatra, Heddy, & Lombardi, 2015; Skinner & Pitzer, 2012).

In recognition of its dynamic nature, some engagement scholars have usefully drawn upon flow theory (Csikszentmihalyi, 1990, 1997) to identify how learners' perceived competence and challenge act as key conditions of engagement (Shernoff, Kelly, Tonks, Anderson, Cavanagh, Sinha, & Abdi, 2016), aligning with situated views of learning (Sfard, 1998) and motivation (Nolen, Horn, & Ward, 2015).

The purpose of this study, then, is to understand learners' experience of engagement in work with data and the conditions that support it. Engagement is understood in terms of cognitive, behavioral, and affective dimensions, and the conditions that support engagement are understood in terms of two subjective components that past research and theory suggest influence engagement: perceived challenge and perceived competence, as well as instructional support for engaging in aspects of work with data. Engagement in work with data is explored in the context of outside-of-school STEM enrichment programs carried out during the summer. In recognition of the challenge of studying engagement in learning environments where factors related to activities, learners, and each of the nine programs all interact at the same time, this study uses a methodological approach suited to studying engagement as a dynamic, multi-faceted experience. Specifically, this study employs the Experience Sampling Method (ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007) where learners answer short questions about their experience when signaled. This approach is both sensitive to changes in engagement over time, as well as between learners and allows us to understand engagement and how factors impact it in more nuanced and complex ways (Turner & Meyer, 2000).

Chapter 2

Literature Review

What is data analysis and what has past research taught us about it? This section defines data analysis as a key practice across STEM domains, with a focus on work with data as activities that are both very specific to work with data (i.e., constructing measures and data modeling) and activities that are more general across STEM domains (i.e., asking questions and interpreting findings). This section also reviews gaps in the literature and introduces engagement and "influencers" of engagement, or factors that past research indicates can impact learners' engagement, to establish the conceptual framework used in the present study.

2.1 Defining Work With Data

As described in the introduction to this section, some scholars have focused on a few key pieces of data analysis connected through the use of "data to solve real problems and to answer authentic questions" (Hancock et al., 1992, p. 337). This approach is commonly described as including two goals: 1) creating data through constructing measures and collecting data and 2) accounting for variability in data through models, or data modeling (English, 2012; Hancock et al., 1992; Lehrer & Romberg, 1996; Lesh et al., 2008). This approach has primarily been taken up by mathematics educators and is reflected in statistics curriculum documents (Franklin et al., 2007). In science settings, where answering questions about phenomena serve as the focus of activities, it shares features of the process of engaging in scientific and engineering practices but has been less often studied.

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

The five aspects of work with data. The definition of working with data used in the present study represents a synthesis across these existing accounts of this process and focuses on five aspects that are common to them. Engagement in work with data, then, includes five processes that are part of a cycle (Franklin et al.,

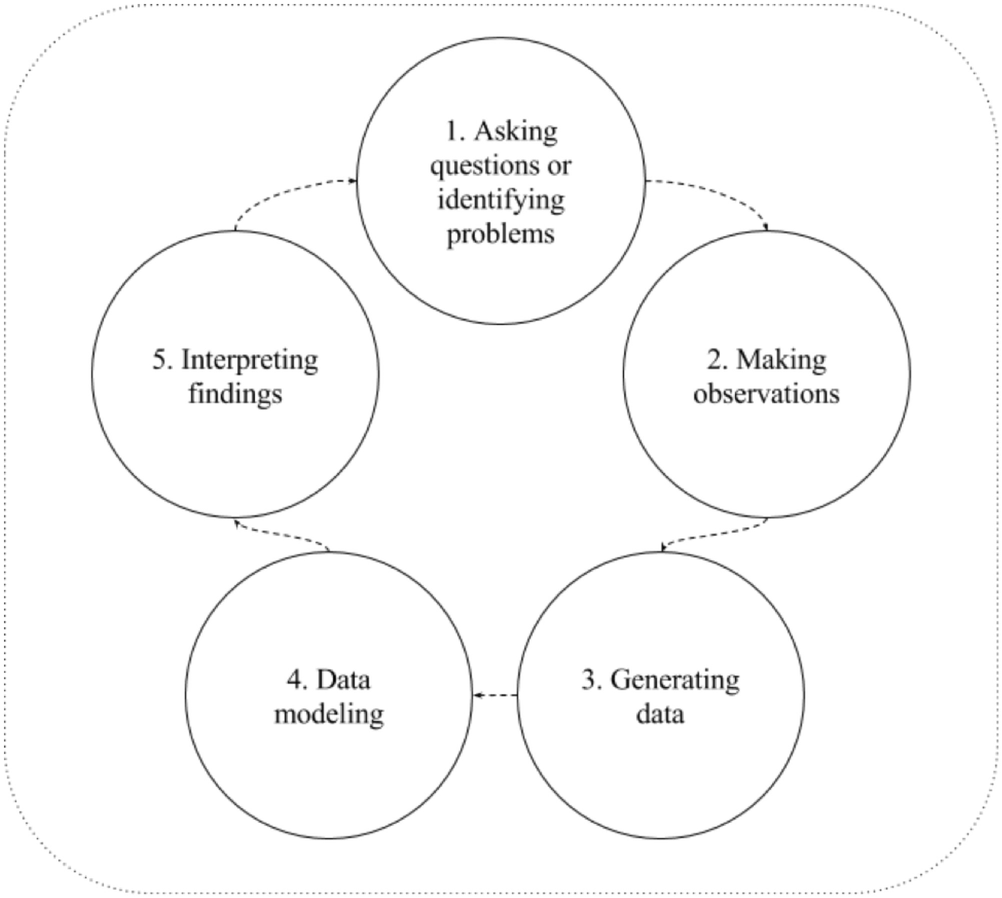


Figure 2.1: Work with data in STEM education settings

2007; Lee & Tran, 2015; Wild & Pfannkuch, 1999). Those processes are: asking questions or identifying problems, making observations, generating data, data modeling (to account for variability or uncertainty), and interpreting and communicating findings.

The five practices depicted in Figure 1, are a cycle because not only does each part follow that before it, but also because the overall process is iterative: interpreting findings commonly leads to new questions and subsequent engagement in work with data. The first process, asking questions, is about generating questions that can be answered with empirical evidence. The next, making observations is about watching phenomena and noticing what is happening with respect to the phenomena or problem being investigated. This is followed by generating data, the process of figuring out how or why to inscribe an observation as data about a phenomena, as well as generating coding frames or tools for measuring. Next, because data are often messy, data modeling is a necessary step follows from its creation or collection. Data models include simple statistics, such as the mean and variance, as well as more complicated models, such as linear models and extensions of the linear model. Finally, the last step is to interpret and communicate findings regarding the phenomena that the question is about.

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

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

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

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

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

2.2 What We Know (And Do Not Know) About Engagement in Work with Data

Research related to engagement in work with data has been carried out by developmental and educational psychologists as well as by mathematics and science educators (see Lehrer and Schauble, 2015, for a review). This research has been carried out in laboratories and classroom settings. For this study, key findings from past studies are organized around three themes: 1. Specific cognitive outcomes 2. Learners' capability to participate in each of the aspects of work with data 3. Strategies to address key challenges of engaging in each of the aspects of work with data

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

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

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

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

2.3 Engagement in STEM Domains

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

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

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

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

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

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

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

2.4 Using ESM to Study the Dynamics of Engagement

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

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

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

2.5 A Person-Oriented Approach to Engagement

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

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

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

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

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

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

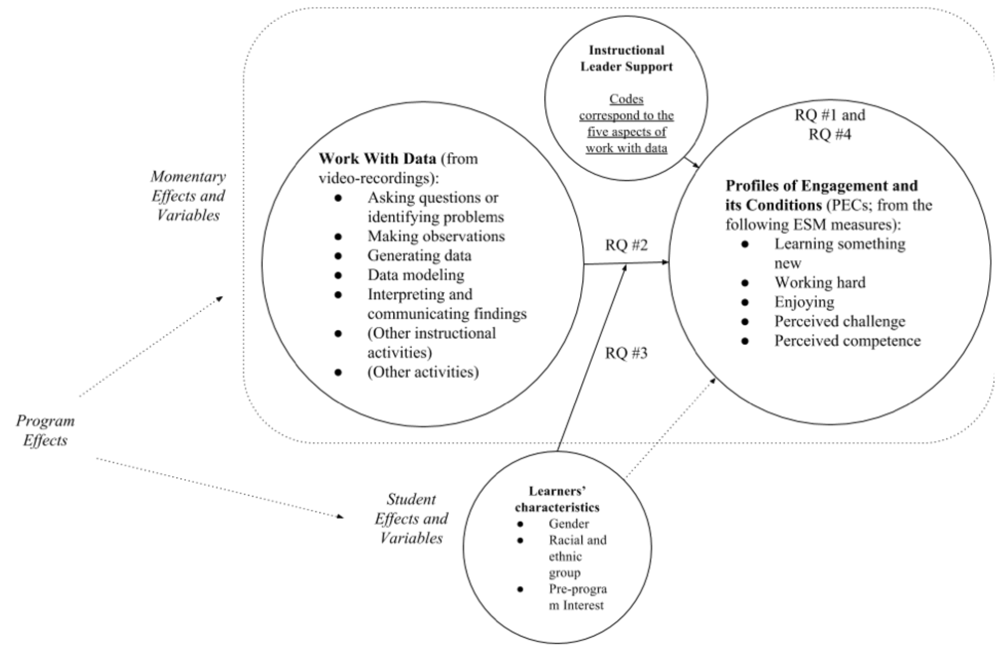


Figure 2.2: A conceptual framework for this study with research questions labeled

2.7 Conceptual Framework

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

There are five aspects of work with data synthesized from past research (i.e., Hancock et al., 1992; Lehrer & Romberg, 1996; Wild & Pfannkuch, 1999): 1. Asking questions or identifying problems 2. Making observations 3. Generating data 4. Data modeling 5. Interpreting and communicating findings

In addition to these five aspects of work with data, two activities that are not part of work with data will be coded so engagement in each aspect of work with data can be compared to other during other times. Other instructional activities, such as listening to a lecture by an instructor, and other activities, such as activities characterized by students being not focused on STEM, off-task, or unfocused. v In this figure, engagement in work with data is associated with different profiles of engagement and its conditions (PECs). The theoretical framework for the person-oriented approach suggests that while the dynamics among the individual aspects of engagement emerge in complex and situation-specific ways, it is possible to consider engagement in terms of patterns among its components. In most settings, a relatively small number of these patterns can be identified in most developmental (and learning-related) settings (Bergman & Magnusson, 1997) and these patterns can be considered in terms of profiles of engagement (Schmidt et al., 2017).

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

2.8 Research Questions

The four research questions are as follows:

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

Chapter 3

Method

This study uses ESM (Hektner et al., 2007) data collected as part of a study of learners' interest and engagement in outside-of-school STEM enrichment programs (Shumow & Schmidt, 2013). It makes use of a sequential exploratory data analysis strategy, in which qualitative data is analyzed to enrich quantitative findings (Creswell, Clark, Gutmann, & Hanson, 2003). In particular, moments in which learners are particularly engaged are identified as part of the quantitative analysis; these moments are then coded qualitatively to identify their common characteristics, first through an inductive step and then through a confirmatory step involving a second rater. While programs have been video-recorded, the video has not been coded for the aspects of work with data, and the other measures from ESM and pre-survey data are to be constructed for this study. ## Participants

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

3.1 Context

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

Students completed a pre-survey before the program. Students also completed pre- and post-course surveys of their experience in STEM, intention to pursue a STEM major or career, and questions for other motivation

Table 3.1: Demographic characteristics of youth

Students	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

and engagement-related measures. At the beginning of the programs, students were introduced to the study and the phones used for data collection related to the ESM. ESM data were collected two days each week, for three weeks (weeks 2-4 of the program). In all of the programs, about equal video-recording time was dedicated to classroom and field experiences. This detail is important because programs associated with one of the intermediaries rotated between classroom and field experience days, while the other used the first half of each day for one (i.e., classroom activities) or the other (i.e., field experience days).

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

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

3.3 Data Sources and Measures

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

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

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

Table 3.3: Measure for pre-program interest in STEM

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

3.3.1 ESM measures of learners' engagement and its conditions

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

3.3.2 Survey measures of pre-interest

Measures of students' pre-interest are used as student-level influencers of PECs. In particular, three items adapted from Vandell, Hall, O'Cadiz, and Karsh (2012) were used, with directions for students to rate their agreement with the items' text using the same scale as the ESM items: Not at all (associated with the number 1 on the survey), A little (2), Somewhat (3), and Very Much (4). The items are presented in Table 4.

3.3.3 Codes for instructional support for work with data from the video-recordings

Different aspects of instructional support for work with data are identified from video-recordings with the use of a coding frame with five for each of the aspects of instructional support for work with data. These codes are developed from the STEM-Program Quality Assessment (STEM-PQA; Forum for Youth Investment, 2012), an assessment of quality programming in after school programs. Specific details on how the measure aligns with the original STEM-PQA on which this measure is based are presented in the appendix.

3.3.4 Demographic variables

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

Table 3.4: Coding Frame for Instructional Support for Work With Data

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

students' racial and ethnic group being Hispanic, African American, Asian or Pacific Islanders, or native American.

3.4 Data Analysis

Before analyzing data to answer the research questions, preliminary analyses are carried out. The steps for both preliminary and the primary analyses are described in this section.

3.4.1 Preliminary analyses

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

3.4.2 Analysis for Research Question #1

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

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

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

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

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

3.4.3 Analysis for Research Question #2

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

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

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

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

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

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

3.4.4 Analysis for Research Question #3

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

3.4.5 Analysis for Research Question #4

To answer this question, on the common characteristics of potentially adaptive PECs, a sequential exploratory data analysis strategy was used. While the activity in terms of the aspects of work with data and the other activities likely predicts differences in PECs, there may be other characteristics that predict PECs, and those characteristics that predict potentially adaptive, or beneficial to students' learning, PECs may be useful to identify both for interpreting findings from the present study and for future research. To answer this question, heterogeneity in terms of how the aspects of work with data relate to the PECs will first be identified. For example, if constructing measures is found to be associated with both potentially adaptive and potentially maladaptive PECs, then videos associated with this aspect of work with data to be interrogated further for this research question. Note that as part of an sequential exploratory mixed methods design, the focus of this qualitative analysis may shift based on what the results of the quantitative analyses suggest.

3.5 Power Analysis

Few publications and tools address the question of statistical power for models with crossed random effects (Westfall, Kenny, & Judd, 2014). To carry out power analysis for detecting the minimum detectable effect for the relationship between one of the aspects of work with data and profiles of engagement, Westfall et al.'s (2017) software Power Analysis for General Anova designs to calculate power for models with arbitrarily complex random effects structures is used. The power, or [replace], was set to 0.80. The results of the power analysis indicated that a minimum detectable d (effect size) is 0.43, a moderate effect (Cohen, 1992).

3.6 Sensitivity Analysis

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

3.7 Limitations

This study has three primary limitations. First, this study does not consider outcomes from engaging, such as the products of neither students' work, nor the specific cognitive capabilities they develop through their participation. Second, the context for this study is suited to understanding engagement in aspects of work with data but not explicitly designed for it, and 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. Third, this program is not representation of all outside-of-school programs, as many of the programs were based on characteristics of model 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 features in terms of their design.

Chapter 4

Preliminary results

4.1 Preliminary analysis

4.1.1 Descriptive statistics for study variables

First, descriptive statistics for all of the study variables–overall pre-interest, the five variables that are used to estimate the PECs, and the variables for each of the five aspects of work with data (which are dichotomous variables)–are presented. Overall pre-interest and the variables used to estimate the PECs are presented first. The composite variable for instructional support for work with data was constructed as the sum of each of the five dichotomous variables that represented the aspects of instructional support for work with data; thus, its possible values ranged between zero and five.

4.1.2 Correlations among study variables

Next, correlations between individual aspects of work with data (and the composite) and the variables that are used to create the PECs are presented. These correlations suggest that the aspects of work with data are not related to the aspects of work with data to a large degree, which is not surprising given the small ICC values for the momentary level, as the aspects of work with data are associated with this level. Most noteworthy is the very small correlations between the aspects of work with data and the profiles; these correlations range (in absolute values) from .00 to .05. Only the relations between communicating and profile six are statistically significant. The composite variable was correlated with the profiles from (in absolute values) 0.002 to 0.035, none statistically significant. The aspects of work with data are modestly correlated with one another, with correlations ranging from .16 to .46; all were significant. The Spearman rank correlations were also considered for all of the correlations that involved the individual aspects of instructional support for work with data; these are presented in the appendix because these were all within a .02 value (i.e., each Spearman's *rho* compared to its corresponding Pearson's *r* was within .02).

Table 4.1: Correlations among study variables

rowname	dm_ask	dm_obs	dm_gen	dm_mod	dm_com	dm_cog_eng	dm_beh_eng	dm_aff_eng	dm_challenge	dm_competence
dm_ask										
dm_obs	.38									
dm_gen	.31	.30								
dm_mod	.42	.19	.35							
dm_com	.42	.20	.38	.50						
dm_cog_eng	.02	.01	.02	.02	.00					
dm_beh_eng	.01	.03	.02	.01	-.02	.60				
dm_aff_eng	.01	-.01	-.03	.01	-.05	.59	.57			
dm_challenge	-.01	-.02	-.01	.03	-.06	.30	.27	.27		
dm_competence	-.01	-.00	-.05	-.00	-.03	.40	.41	.47	.08	

Table 4.2: Proportion of signals for which each of the aspects of work with data was present

Aspect	Proportion
Asking Questions	0.389
Making Observations	0.258
Generating Data	0.453
Data Modeling	0.288
Communicating Findings	0.470

From the coding with the STEM-PQA, work with data appears common. Out of the 248 segments, 236 were coded for instructional support for work with data; for the other, not-coded segments, issues with the video-recordings were the primary source of the missing data; in these cases, students may have still replied to signals, but it was not possible to code for instructional support for work with data associated with these responses.

4.2 Statistical software developed

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

Chapter 5

Results for Research Question #1

5.1 Frequency of work with data

From the coding with the STEM-PQA, work with data appears common. Out of the 248 segments, 236 were coded for instructional support for work with data; for the other, not-coded segments, issues with the video-recordings were the primary source of the missing data; in these cases, students may have still replied to signals, but it was not possible to code for instructional support for work with data associated with these responses.

Table 5.1: Proportion of signals for which each of the aspects of work with data was present

Aspect	Proportion
Asking Questions	0.389
Making Observations	0.258
Generating Data	0.453
Data Modeling	0.288
Communicating Findings	0.470

Chapter 6

Results for Research Question #2

6.1 Statistical software developed

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

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

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

6.2.1 Exploration of a wide range of models a

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

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

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

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

6.2.2 In-depth statistics for particular models

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

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

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

Table 6.1: 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)

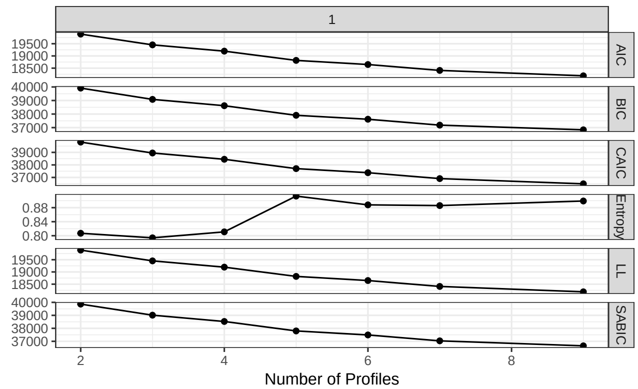


Figure 6.1: Fit statistics for model 1 solutions

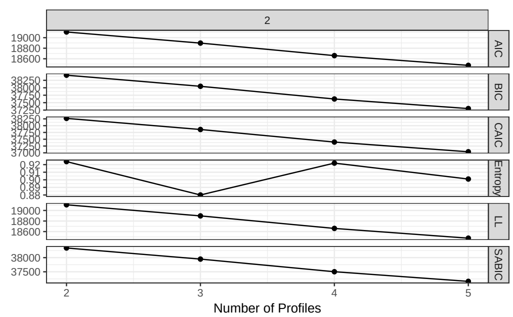


Figure 6.2: Fit statistics for model 2 solutions

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.

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.

6.2.3 Comparison of model 1 and model 2 type solutions

When looking across solutions, some overall patterns in terms of what profiles emerge and some directions for which models are to be selected for use in subsequent analysis can be identified. First, overall patterns are discussed. In the table, which profiles emerge from which solution is presented.

There is a wide range of profiles. Some appear very commonly, particularly those (full and universally low) characterized by high or low levels across all of the variables. Moderate profiles, both all moderate (characterized by moderately high levels across all of the variables) and moderately low (characterized by low levels across all of the variables), also appeared commonly, particularly for the solutions for model 1.

Table 6.2: Profile assignments by LPA solution (models and numbers of profiles)

Number of Profiles	Full	All Moderate	Comptent but not Engaged or Challenged	Only Behavioral	Only Affective	Moderately Low	Engaged and Competent but not Challenged	Challenged but not Engaged or Comptent	Challenged	Highly Challenged	Universally Low	Comptent but not Challenged
Model 1												
3	x	x									x	
4	x	x									x	x
5	x	x		x	x						x	
6	x	x		x	x		x				x	
6 (alt)	x					x	x		x	x	x	
7	x					x		x	x	x	x	x
Model 2												
7 (alt)	x					x		x	x	x	x	x
3									x		x	x
4							x		x	x	x	
5	x	x								x	x	x

6.2.4 Examination of specific candidate models

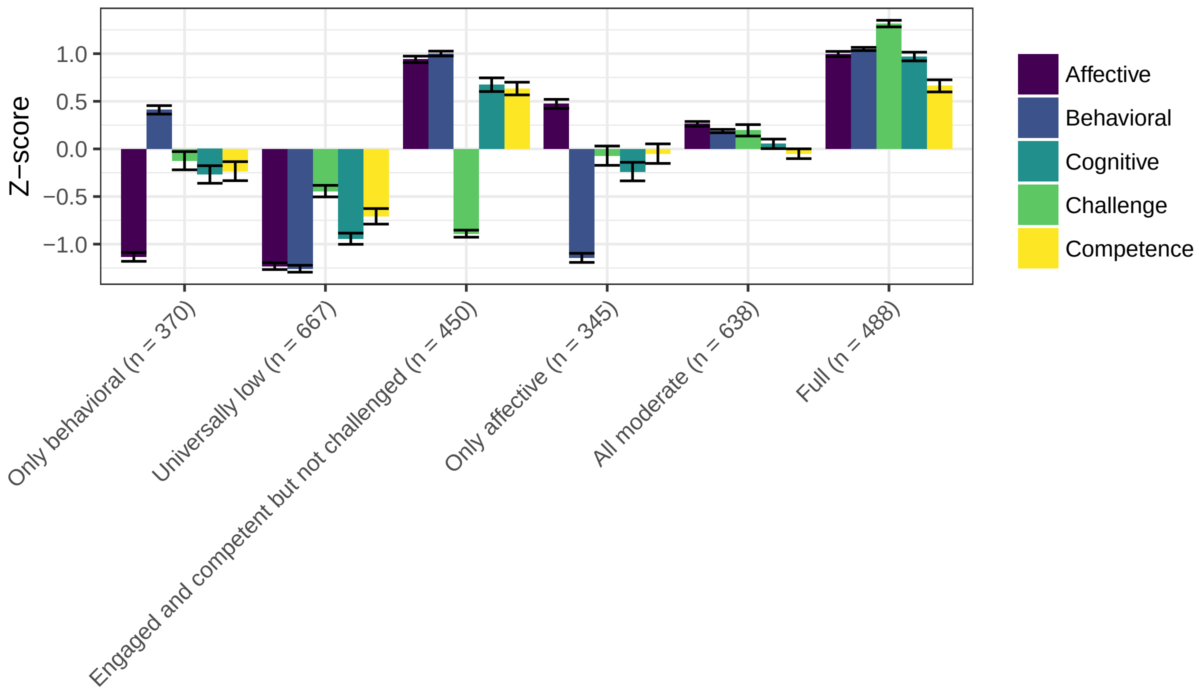
Following from the in-depth exploration of the candidate solutions, in this section, model solutions associated with specific model types and the number of profiles are investigated. In particular, the model one type, six profile, and model one type, seven profile solutions are described. Descriptions of other candidate solutions is included in the appendix. For all of the solutions, the raw data and the data that are centered to have a mean equal to 0 and a standard deviation of 1 (thus, the y-axis on each of the plots is labeled "Z-score").

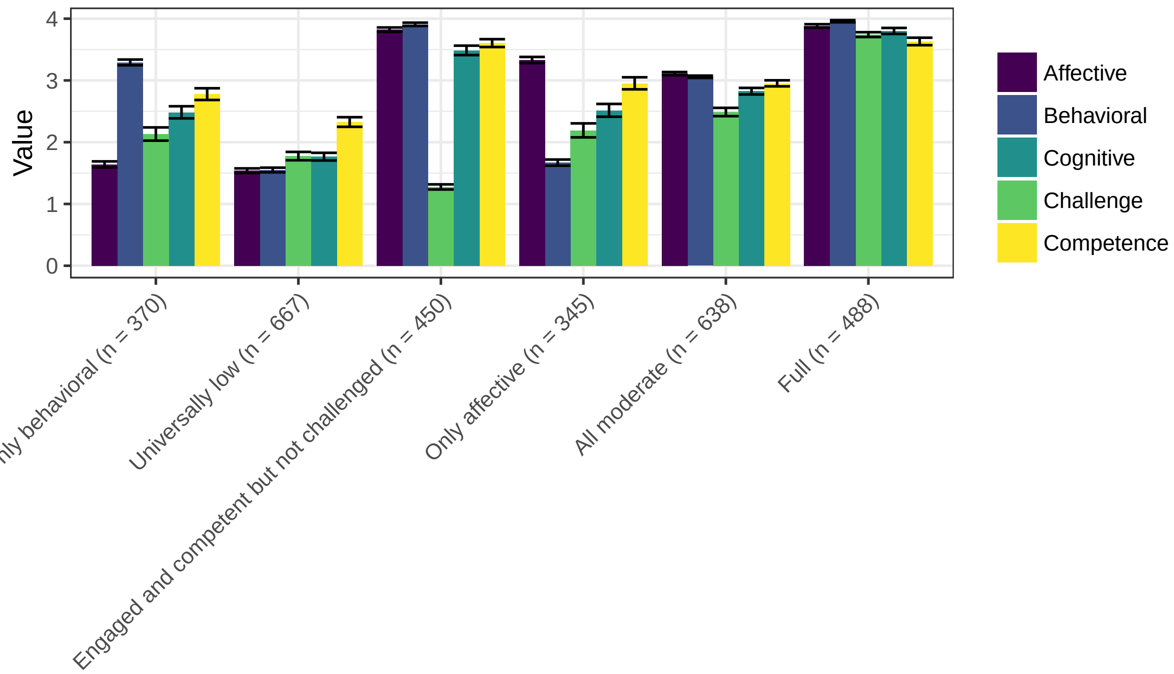
6.2.4.1 Model type: 1, Profiles: 6

This solution is characterized by:

- A *full* profile, profile 6
- An *universally low* profile, profile 2
- An *all moderate* profile, profile 5–and, like, the model 1, six profile solution–with moderate levels of affective engagement
- An *only behaviorally engaged* profile, profile 1, with moderate levels of behavioral engagement, very low affective engagement, and moderately (low) levels of cognitive engagement and challenge and competence
- An *only affectively engaged* profile, profile 4, with moderate levels of affective engagement, low levels of behavioral engagement, and moderately (low) levels of cognitive engagement and challenge and competence
- An *engaged and competent but not challenged* profile, profile 3, characterized by high levels of each of the three dimensions of engagement and of competence, but with low levels of challenge

The number of observations associated with each of the profiles is somewhat balanced, with the universally low profile with the largest number of observations (n = 667; the same number for this profile as in the model 1, five profile solution), followed by the all moderate profile (n = 638). Each of the other four profiles were associated with 300 to 400 observations. Unlike the model 1, four and five profile solutions, which distinguished observations on *either* a condition of engagement (i.e., competence) or one of its dimensions (i.e., cognitive, behavioral, and affective), this solution was associated with profiles that distinguished observations on the basis of both: There were profiles for only behaviorally and affectively engaged and for engaged and competent but not challenged. This solution is compelling because it appears to group students on the basis of multiple of the indicators, and demonstrate viability on the basis of the fit statistics (i.e., the tables and figure). The log-likelihood was replicated two times, with the next lowest log-likelihood not being replicated, followed by a log-likelihood that was replicated (at least) seven times. This solution (associated with the log-likelihood that was replicated [at least] seven times) could be investigated in further detail, to see whether–and if so, how–it differs from the solution interpreted here. This solution is a strong candidate for use in subsequent analyses.



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## Error: 'i.out' does not exist in current working directory ('/Users/joshuarosenberg/Google Drive/1_Re
```

6.2.4.2 Model type: 1, Profiles: 7

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.

6.2.4.3 Looking across model 1 and model 2 type solutions

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 may be preferred and is selected for use in subsequent analyses.

As a type of sensitivity analysis focused on alternate model specifications (different from the kind described earlier for quantifying how robust an inference is to potential sources of bias or confounding variables, e.g. Frank, 2003), the model 1, seven profile solution is also explored, but results for it are included in the appendix. This model is less restrictive but does not meet the assumption of independence; some scholars refer to it, as such, as a general or Guassian mixture model solution, instead of an LPA solution (Bauer, 2004). Because covariances are estimated, relationships between the variables not captured in their mean levels estimated for each profile are also estimated. This suggests that these models may be modeling different relations between the variables than those associated with model 1 and that they may fit the data better, but they are also more complex and so should be interpreted with consideration these added parameters.

Chapter 7

Results for Research Question #3

7.1 Results for Research Question #3: How do data practices relate to youth engagement in the programs?

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

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

7.1.1 Null models

The null models presented in the table provide insight into the levels at which predictors may be able to explain the outcome. For all six profiles, the ICCs were very small, from 0.00 to 0.023. This suggests that very little variability can be explained simply by the program. For the momentary level, the ICCs were also very small, ranging from 0.004 to 0.011. Finally, the youth-level ICCs ranged from .099 to .427. Looking across these values, considering variability at the program, momentary, and youth levels, most of the explained variability in the responses is associated with youth; the program and momentary levels were associated with very small values, suggesting that variables at these levels have minimal variability that is able to be explained. In turn, this suggests that these variables, including those for instructional support for work with data, may not have strong effects in terms of their relations with the PECs.

In terms of specific ICCs at the youth level, the value for the youth-level ICC was highest for the *full* profile, 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 ICC, .265. Finally, a large amount of variability is associated with the residual (variance that is not associated with the program, momentary, or youth levels). This suggests that there is wide variation in students' responses that may not be readily explained or predicted.

7.1.2 Models with variables for aspects of instructional support for work with data added separately

When the predictor variables for work with data are added, some overall patterns and specific findings can be identified. The only relations with p-values that were below the criterion for statistical significance (.05) were for the relations between modeling data and the *full* profile ($B = 0.036$ (0.016), $p = .016$) and between generating data and the full profile ($B = 0.029$ (0.015), $p = .024$).

Adding these variables changed the (conditional upon the random effects) r-squared values from, .002 to .018, very small changes suggesting that the aspects of work with data do not strongly predict the PECs. This is in-line with the correlations for these variables with those variables that make up the profiles, and the ICC values at the momentary level.

The sensitivity analysis for the effect of generating data suggested that 1.884% of the inference would have to be due to bias to invalidate the inference, suggesting that this effect is not very robust to potential sources of bias, such as an omitted (in this analysis) confounding (or control) variable. For the effect of modeling, 9.835% would need to be due to bias to invalidate the inference. This effect, then, is less sensitive to possible sources of bias, but is still not highly robust.

Table 7.1: Results of mixed effects models for instructional support for work with data as separate variables

model	intercept	dm_ask	dm_obs	dm_gen	dm_mod	dm_com	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.1 (0.014) ($p < .001$)	0.013 (0.014) ($p = 0.188$)	0.017 (0.014) ($p = 0.122$)	0.009 (0.014) ($p = 0.244$)	-0.026 (0.015) ($p = 0.957$)	0.025 (0.014) ($p = 0.043$)	0.008	0.097	0.007
Universally low	0.231 (0.029) ($p < .001$)	-0.008 (0.017) ($p = 0.685$)	0.01 (0.017) ($p = 0.277$)	-0.017 (0.017) ($p = 0.839$)	0.007 (0.018) ($p = 0.356$)	-0.006 (0.017) ($p = 0.626$)	0.005	0.269	0.026
Engaged and competent but not challenged	0.148 (0.016) ($p < .001$)	-0.012 (0.015) ($p = 0.797$)	0.009 (0.015) ($p = 0.267$)	-0.016 (0.014) ($p = 0.871$)	0.001 (0.015) ($p = 0.487$)	0.008 (0.014) ($p = 0.284$)	0.017	0.305	0.000
Only affective	0.115 (0.011) ($p < .001$)	0.005 (0.013) ($p = 0.362$)	-0.019 (0.013) ($p = 0.919$)	-0.015 (0.013) ($p = 0.874$)	-0.011 (0.014) ($p = 0.787$)	0.012 (0.013) ($p = 0.175$)	0.000	0.100	0.000
All moderate	0.234 (0.02) ($p < .001$)	0.016 (0.017) ($p = 0.169$)	0.001 (0.016) ($p = 0.477$)	0.015 (0.016) ($p = 0.169$)	-0.007 (0.017) ($p = 0.651$)	-0.009 (0.016) ($p = 0.716$)	0.005	0.260	0.005
Full	0.171 (0.025) ($p < .001$)	-0.017 (0.015) ($p = 0.859$)	-0.024 (0.015) ($p = 0.943$)	0.029 (0.015) ($p = 0.025$)	0.035 (0.016) ($p = 0.016$)	-0.03 (0.015) ($p = 0.976$)	0.028	0.455	0.019

7.1.3 Models with the composite added

For the composite of work with data, the composite predicted the profile for *only behavioral* (B = 0.007 (0.004), p = .021), but not any of the other profiles. However, this coefficient is very small in practical terms, and 12.261% would need to be due to bias to invalidate the inference. The change in r-squared values ranged from .003 to .020, suggesting minimal potential relations among factors (such as support for work with data as measured by the composite variable) at the momentary level. When the composite was treated as a dichotomous (instead of a continuous) variable, so that the variable takes a value of one if any of the aspects of work with data are present, the results are similar in terms of the magnitude of the effects and their significance, as none of the relations are statistically significant when the dichotomous variable is used.

Table 7.2: Results of mixed effects models for the composite

model	intercept	dm_composite	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.104 (0.014) (p < .001)	0.007 (0.004) (p = 0.021)	0.008	0.097	0.008
Universally low	0.229 (0.029) (p < .001)	-0.003 (0.004) (p = 0.784)	0.004	0.269	0.026
Engaged and competent but not challenged	0.148 (0.016) (p < .001)	-0.002 (0.004) (p = 0.754)	0.016	0.305	0.000
Only affective	0.117 (0.011) (p < .001)	-0.005 (0.003) (p = 0.912)	0.000	0.100	0.000
All moderate	0.234 (0.02) (p < .001)	0.003 (0.004) (p = 0.212)	0.005	0.259	0.005
Full	0.168 (0.025) (p < .001)	-0.001 (0.004) (p = 0.599)	0.030	0.452	0.021

7.1.4 Summary of findings for research question #2

When looking across findings, we find few relations between instructional support for work with data and the profiles, though there were notable effects of modeling, though they were small effects (i.e., when students are doing this, they are around 3% more likely to be responding in a way associated with the *full* profile). The composite for work with data had a relation of around 0.01 with the *only behavioral* profile, suggesting that for each one-value increase in the composite (which has a range from one to five), this profile is around 1% more likely. These findings are similar to those obtained when the model 1 type, seven profile solution is used for the outcome variables; see the appendix for more detail. Broadly, further explanations and investigations of these effects –focusing on the characteristics of instructional support for work with data in the context of summer STEM programs and how this support is measured in terms of codes from the video–are the focus on research question #4 and are discussed in the next chapter. Moreover, these findings are deepened in subsequent analyses for research questions #3.

Chapter 8

Results for Research Question #4

8.1 Results for Research Question #4: How do youth characteristics relate to their engagement in summer STEM programs?

Research question #3 is focused on how the relationships of instructional support for work with data differ on the basis of pre-program interest and other youth characteristics. Like for the previous two research questions, linear models that account for the cross-classification of the moment and the youth–and their nesting within the programs–are used. Findings from models with pre interest, gender, and URM status are first presented. Then, models with these variable and the individual aspects and composite of work with data are added and then models with the interaction between these characteristics and the composite.

8.1.1 Models with pre interest, gender, and under-represented minority (URM) status

These results show that overall pre-interest is associated with the *engaged and competent but not challenged* profile ($B = 0.039$ (0.021), p = .009). The effect of being a female has a relation of 0.059 (0.036, p = .054) upon the probability of a response being associated with the *universally low* profile; though this effect did not meet the criteria for statistical significance, sensitivity analysis to determine how much more robust the effect would need to be to make an inference. For the effect of overall pre-interest upon the *engaged and competent but not challenged* profile, 17.879% would be needed to invalidate the inference, suggesting a moderately robust effect. For the effect of gender upon the *universally low* profile, 16.996% of the bias would need to be removed (or the effect would need to be larger by this percentage) to sustain the inference. The change in r-squared values ranged from .004 to .007, suggesting that pre-interest and other individual characteristics - in addition to the aspects of work with data - have minimal relations with the PECs. Thai is more surprising than the similarly minimal relations observed for work with data: as the null models indicate, there were large ICCs (a large proportion of the variability in the outcome variables) at the youth-level (as pre-interest, gender, and URM status are variables associated with this level) This is discussed further in the next chapter.

Table 8.1: Results of mixed effects models with interest and other characteristics

model	intercept	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.131 (0.044) (p = 0.002)	-0.014 (0.011) (p = 0.89)	0.018 (0.019) (p = 0.168)	0.025 (0.026) (p = 0.168)	0.006	0.091	0.012
Universally low	0.33 (0.084) (p < .001)	-0.042 (0.021) (p = 0.974)	0.059 (0.036) (p = 0.054)	-0.003 (0.051) (p = 0.525)	0.005	0.276	0.012
Engaged and competent but not challenged	0.017 (0.062) (p = 0.392)	0.039 (0.016) (p = 0.009)	0.026 (0.028) (p = 0.18)	-0.011 (0.04) (p = 0.613)	0.014	0.306	0.000
Only affective	0.075 (0.042) (p = 0.037)	0.009 (0.011) (p = 0.214)	-0.022 (0.018) (p = 0.883)	0.025 (0.025) (p = 0.159)	0.011	0.094	0.005
All moderate	0.374 (0.073) (p < .001)	-0.016 (0.019) (p = 0.806)	-0.037 (0.032) (p = 0.872)	-0.077 (0.046) (p = 0.952)	0.005	0.258	0.006
Full	0.084 (0.08) (p = 0.149)	0.019 (0.02) (p = 0.17)	-0.036 (0.036) (p = 0.842)	0.043 (0.051) (p = 0.2)	0.030	0.452	0.001

8.1.2 Models with pre interest, gender, and URM status and the aspects of work with data

These results show very similar patterns to those observed in the models with pre-interest and the other individual characteristics and the models with the aspects of work with data separate. Like in the models with only pre-interest and the other individual characteristics, pre-interest is related to the *only behavioral* profile ($B = 0.039$ (0.016), p = .009). Being female is again related but not to a level that it meets the criteria for statistical significance ($B = 0.06$ (0.037), p = .051). Generating data ($B = 0.027$ (0.015), p = .033) and modeling data ($B = 0.034$ (0.017), p = .020) were both related to the *full* profile to a similar extent and with similar robustness as found in the separate models. Compared to the null models, the r-squared values changed from .001 to .029, suggesting small improvements from the additions of the individual characteristics and the codes for the aspects of work with data.

Table 8.2: Results of mixed effects models with interest and other characteristics and the aspects of work with data

model	intercept	dm_ask	dm_obs	dm_gen	dm_mod	dm_com	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.107 (0.045) (p = 0.01)	0.015 (0.015) (p = 0.158)	0.013 (0.015) (p = 0.191)	0.014 (0.014) (p = 0.17)	-0.023 (0.016) (p = 0.929)	0.018 (0.015) (p = 0.115)	-0.013 (0.012) (p = 0.873)	0.019 (0.019) (p = 0.159)	0.031 (0.026) (p = 0.122)	0.008	0.095	0.010
Universally low	0.356 (0.086) (p < .001)	-0.015 (0.018) (p = 0.789)	0.003 (0.018) (p = 0.427)	-0.014 (0.017) (p = 0.789)	0.004 (0.019) (p = 0.407)	0.002 (0.018) (p = 0.461)	-0.047 (0.022) (p = 0.982)	0.06 (0.037) (p = 0.051)	-0.01 (0.052) (p = 0.575)	0.005	0.276	0.015
Engaged and competent but not challenged	0.022 (0.063) (p = 0.362)	-0.011 (0.015) (p = 0.763)	0.009 (0.015) (p = 0.266)	-0.014 (0.014) (p = 0.833)	0 (0.015) (p = 0.504)	0.004 (0.015) (p = 0.404)	0.039 (0.016) (p = 0.009)	0.025 (0.028) (p = 0.188)	-0.012 (0.04) (p = 0.614)	0.015	0.304	0.000
Only affective	0.09 (0.04) (p = 0.015)	0.004 (0.014) (p = 0.397)	-0.017 (0.014) (p = 0.886)	-0.02 (0.013) (p = 0.938)	-0.012 (0.015) (p = 0.8)	0.016 (0.014) (p = 0.124)	0.007 (0.01) (p = 0.264)	-0.02 (0.018) (p = 0.867)	0.018 (0.025) (p = 0.234)	0.000	0.095	0.001
All moderate	0.354 (0.075) (p < .001)	0.023 (0.017) (p = 0.09)	0.007 (0.017) (p = 0.342)	0.012 (0.016) (p = 0.233)	-0.004 (0.018) (p = 0.593)	-0.011 (0.017) (p = 0.747)	-0.012 (0.019) (p = 0.743)	-0.038 (0.033) (p = 0.875)	-0.076 (0.046) (p = 0.95)	0.005	0.256	0.007
Full	0.094 (0.083) (p = 0.132)	-0.019 (0.016) (p = 0.887)	-0.025 (0.016) (p = 0.94)	0.027 (0.015) (p = 0.033)	0.034 (0.017) (p = 0.02)	-0.027 (0.016) (p = 0.956)	0.018 (0.021) (p = 0.195)	-0.035 (0.037) (p = 0.827)	0.043 (0.053) (p = 0.207)	0.027	0.476	0.002

8.1.3 Models with pre-interest, gender, and URM status and work with data composite

Like for the individual aspects, these models with the composite for work with data instead of the individual aspects. These results show very similar patterns to those observed in the models with pre-interest and the other individual characteristics and the models with the aspects of work with data separate. Like in the models with only pre-interest and the other individual characteristics alone (and like in the model with the individual aspects), pre-interest is related to the *only behavioral* profile ($B = 0.039$ (0.016), p = .009). Being female is again related but not to a level that it meets the criteria for statistical significance ($B = 0.06$ (0.037), p = .052). The composite was significantly related to the *only behavioral* profile ($B = 0.007$ (0.004), p = .027) to a similar extent and with similar robustness as found in the separate model. Compared to the null models, the r-squared values changed from .008 to .026, once again suggesting small improvements from the additions of the individual characteristics and the composite for the aspects of work with data.

Table 8.3: Results of mixed effects models with interest and other characteristics and the composite work with data

model	intercept	dm_composite	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.111 (0.045) (p = 0.008)	0.007 (0.004) (p = 0.027)	-0.013 (0.012) (p = 0.874)	0.02 (0.019) (p = 0.149)	0.03 (0.026) (p = 0.126)	0.007	0.095	0.010
Universally low	0.355 (0.086) (p < .001)	-0.004 (0.005) (p = 0.824)	-0.047 (0.022) (p = 0.983)	0.06 (0.037) (p = 0.052)	-0.01 (0.052) (p = 0.573)	0.003	0.277	0.015
Engaged and competent but not challenged	0.022 (0.063) (p = 0.364)	-0.003 (0.004) (p = 0.783)	0.039 (0.016) (p = 0.009)	0.025 (0.028) (p = 0.19)	-0.011 (0.04) (p = 0.608)	0.014	0.305	0.000
Only affective	0.094 (0.041) (p = 0.012)	-0.005 (0.003) (p = 0.93)	0.006 (0.01) (p = 0.293)	-0.02 (0.018) (p = 0.863)	0.019 (0.025) (p = 0.226)	0.000	0.095	0.002
All moderate	0.354 (0.075) (p < .001)	0.005 (0.004) (p = 0.111)	-0.012 (0.019) (p = 0.743)	-0.037 (0.033) (p = 0.872)	-0.076 (0.046) (p = 0.95)	0.005	0.256	0.008
Full	0.089 (0.083) (p = 0.144)	-0.001 (0.004) (p = 0.62)	0.019 (0.021) (p = 0.184)	-0.037 (0.037) (p = 0.84)	0.044 (0.053) (p = 0.205)	0.029	0.473	0.002

8.1.4 Models with interactions between pre interest, gender, and URM status and work with data composite

These results show similar patterns to the earlier models.Like in the models with only pre-interest and the other individual characteristics alone (and like in the model with the individual aspects), pre-interest is related to the *only behavioral* profile ($B = 0.033$ (0.018), p = .033). Being female is again related but not to a level that it meets the criteria for statistical significance ($B = 0.064$ (0.041), p = .059). With the interactions added, the composite was no significantly related to the *only behavioral* profile ($B = 0.016$ (0.016), p = .156) to a similar extent and with similar robustness as found in the separate model. One interaction, between pre-interest and being female, had a significant effect upon the profile for *full* engagement ($B = 0.012$ (0.006), p = .026). However, only 1.953% of the effect would need to be due to bias to invalidate the inference. The r-squared values, relative to the models with only random effects (the null models), increased from .003 to .028, again suggesting small effects of the predictors upon the PECs.

Table 8.4: Results of mixed effects models with the interactions between interest and other characactistics and the composite for work with data

model	intercept	dm_composite	overall_pre_interest	gender_female	urm	overall_pre_interest:dm_composite	dm_composite:gender_female	dm_composite:urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Only behavioral	0.095 (0.054) (p = 0.041)	0.016 (0.016) (p = 0.156)	-0.01 (0.014) (p = 0.764)	0.018 (0.024) (p = 0.219)	0.04 (0.033) (p = 0.114)	-0.002 (0.004) (p = 0.655)	0.001 (0.007) (p = 0.458)	-0.005 (0.01) (p = 0.691)	0.008	0.095	0.010
Universally low	0.373 (0.093) (p < .001)	-0.013 (0.019) (p = 0.756)	-0.051 (0.024) (p = 0.982)	0.064 (0.041) (p = 0.059)	-0.018 (0.057) (p = 0.623)	0.002 (0.005) (p = 0.335)	-0.002 (0.009) (p = 0.575)	0.004 (0.012) (p = 0.361)	0.004	0.276	0.015
Engaged and competent but not challenged	0.021 (0.068) (p = 0.378)	-0.002 (0.015) (p = 0.559)	0.033 (0.018) (p = 0.033)	0.041 (0.031) (p = 0.093)	0.002 (0.044) (p = 0.479)	0.003 (0.004) (p = 0.22)	-0.008 (0.007) (p = 0.885)	-0.006 (0.009) (p = 0.753)	0.015	0.303	0.000
Only affective	0.078 (0.05) (p = 0.059)	0.003 (0.015) (p = 0.424)	0.018 (0.013) (p = 0.078)	-0.02 (0.023) (p = 0.813)	-0.008 (0.031) (p = 0.604)	-0.006 (0.004) (p = 0.946)	-0.001 (0.007) (p = 0.539)	0.013 (0.009) (p = 0.079)	0.000	0.096	0.002
All moderate	0.337 (0.082) (p < .001)	0.013 (0.018) (p = 0.236)	-0.013 (0.021) (p = 0.731)	-0.043 (0.036) (p = 0.882)	-0.052 (0.051) (p = 0.842)	0 (0.005) (p = 0.476)	0.003 (0.008) (p = 0.344)	-0.012 (0.011) (p = 0.864)	0.005	0.256	0.008
Full	0.119 (0.087) (p = 0.087)	-0.017 (0.014) (p = 0.886)	0.016 (0.022) (p = 0.232)	-0.061 (0.039) (p = 0.94)	0.032 (0.056) (p = 0.283)	0.002 (0.004) (p = 0.337)	0.012 (0.006) (p = 0.026)	0.005 (0.009) (p = 0.264)	0.029	0.476	0.001

8.1.5 Summary of findings for research question #3

When looking across findings, we find minimal relations between pre-interest and other individual characteristics. In particular, we found that pre-interest was related to the *engaged and comptent but not challenged* profile to a modest extent. Being female did not demonstrate statistically significant relations with the *univerally low* profile, though some moderately-sized effects that were nearly statistically significant were observed and interpreted in terms of how much bias would need to be reduced (or how much the larger the effect would need to be) in order for this relation to be statistically significant. These results, like those for research question #2, are similar to those obtained when the model 1 type, seven profile solution is used for the outcome variables. There were few interactive effects observed; the magnitude of the effect of the composite and gender interaction was small (as were the changes in the r-squared value as a consequence of adding this interaction), and the effect appears to not be highly robust to potential sources of bias. Like for research question #2, reasons for why this may be are explored in the next chapter. The effect of the activity appears robust, as in research question #3.

Chapter 9

Discussion

9.0.1 Key Findings

9.0.1.0.1 The nature of engagement in summer STEM programs

We can identify profiles of engagement …

9.0.1.0.2 What explains PECs

Engagement varies from moment-to-moment …

9.0.1.0.3 Summer STEM programs as a context for work with data

9.0.2 Limitations of the Study

9.0.2.0.1 Measurement issues

How instructional support for work with data was measured seems to have been an issue, given the qualitative coding …

9.0.2.0.2 Context issues

These programs were not designed to support work with data …

9.0.3 Recommendations for Future Research

9.0.3.0.1 Explore work with data in settings designed to support it

There are increasingly "data camps" …

9.0.3.0.2 Measure student work with data as well as instructional support for work with data

Measuring what students do in addition to what teachers do is important …

9.0.3.0.3 Explore changes in longer-term outcomes

Changes in longer-term outcomes, such as future plans and goals, are an important goal for summer STEM educators and other stakeholders in such programs …

9.0.4 Implications for Practice

9.0.4.0.1 Engage students in complete cycles of investigation

9.0.4.0.2 Support engagement in specific moments

Viewing engagement in work with data in terms of engagement can help us to build the knowledge base around key data analytic practices for learners. In STEM settings, being engaged predicts key learning-related outcomes (Sinatra et al., 2015). As a consequence, what learners are thinking, feeling, and doing while engaged in work with data, and how challenged or good at data doing any or all of the aspects of work with data they perceive themselves to be, may important predictors of key outcomes and learners' preparation for future learning (Bransford & Schwartz, 1999), especially for learning in data-rich areas of studies and occupations, such as data science. 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.

Chapter 10

References

Akiva, T. (2005). Turning training into results: The new youth program quality assessment. High/Scope Resource, 24(2), 21-24.
Bergman, L. R., & Magnusson, D. (1997). A person-oriented approach in research on developmental psychopathology. Development and psychopathology, 9(2), 291-319.
Bergman, L. R., Magnusson, D., & El Khouri, B. M. (2003). Studying individual development in an interindividual context: A person-oriented approach. Psychology Press.
Berland, L. K., Schwarz, C. V., Krist, C., Kenyon, L., Lo, A. S., & Reiser, B. J. (2016). Epistemologies in practice: Making scientific practices meaningful for students. Journal of Research in Science Teaching, 53(7), 1082-1112.
Bielik, T., & Yarden, A. (2016). Promoting the asking of research questions in a high-school biotechnology inquiry-oriented program. International Journal of STEM Education, 3(1), 15.
Breckenridge, J. N. (2000). Validating cluster analysis: Consistent replication and symmetry. Multivariate Behavioral Research, 35(2), 261-285.
Bystydzienski, J. M., Eisenhart, M., & Bruning, M. (2015). High school is not too late: Developing girls' interest and engagement in engineering careers. Career Development Quarterly, 63(1), 88–95. http://doi.org/10.1002/j.2161-0045.2015.00097.x Cohen, J. (1992). A power primer. Psychological Bulletin, 112(1), 155.
National Governors Association Center for Best Practices, Council of Chief State School Officers. (2010). Common Core State Standards for Mathematics. Washington, DC: National Governors Association Center for Best Practices and the Council of Chief State School Officers.
Corpus, J. H., & Wormington, S. V. (2014). Profiles of intrinsic and extrinsic motivations in elementary school: A longitudinal analysis. The Journal of Experimental Education, 82(4), 480-501.
Csikszentmihalyi, M. (1990). Flow: The psychology of optimal performance. Cambridge, England: Cambridge University Press.
Csikszentmihalyi, M. (1997). Finding flow: The psychology of engagement with everyday life. New York, NY: Basic Books.
Creswell, J. W., Plano Clark, V. L., Gutmann, M. L., & Hanson, W. E. (2003). Advanced mixed methods research designs. In A. Tashakkori & C. Teddlie (Eds.), Handbook of mixed methods in social and behavioral research (pp. 209–240). Thousand Oaks, CA: Sage.
English, L. D. (2012). Data modelling with first-grade students. Educational Studies in Mathematics, 81(1), 15-30.
Finzer, W. (2013). The data science education dilemma. Technology Innovations in Statistics Education, 7(2), p. 1-9.
Forum for Youth Investment. (2012). Youth Program Quality Assessment. Washington, DC: The Forum for Youth Investment Franklin, C., Kader, G., Mewborn, D., Moreno, J., Peck, R., Perry, M., & Scheaffer, R. (2007). Guidelines for assessment and instruction in statistics education (GAISE) report. Alexandria, VA: American Statistical Association.
Fredricks, J. A., & McColskey, W. (2012). The measurement of student engagement: A comparative

analysis of various methods and student self-report instruments. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), The handbook of research on student engagement (pp. 763–782). New York: Springer Science. https://doi.org/10.1007/978-1-4614-2018-7_37

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74(1), 59-109.

Fredricks, J. A., Filsecker, M., & Lawson, M. A. (2016). Student engagement, context, and adjustment: Addressing definitional, measurement, and methodological issues. Learning & Instruction, 43, 1-4.

Gelman, S. A., & Markman, E. M. (1987). Young children's inductions from natural kinds: The role of categories and appearances. Child Development, 58(6), 1532-1541.

Gopnik, A., & Sobel, D. M. (2000). Detecting blickets: How young children use information about novel causal powers in categorization and induction. Child Development, 71(5), 1205-1222.

Gopnik, A., Sobel, D. M., Schulz, L. E., & Glymour, C. (2001). Causal learning mechanisms in very young children: two-, three-, and four-year-olds infer causal relations from patterns of variation and covariation. Developmental Psychology, 37(5), 620.

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. Educational Psychologist, 50(1), 14-30.

Greene, K. M., Lee, B., Constance, N., & Hynes, K. (2013). Examining youth and program predictors of engagement in out-of-school time programs. Journal of Youth and Adolescence, 42(10), 1557-1572.

Hancock, C., Kaput, J. J., & Goldsmith, L. T. (1992). Authentic inquiry with data: Critical barriers to classroom implementation. Educational Psychologist, 27(3), 337-364.

Harring, J. R., & Hodis, F. A. (2016). Mixture modeling: Applications in educational psychology. Educational Psychologist, 51(3-4), 354-367.

Hasson, E., & Yarden, A. (2012). Separating the research question from the laboratory techniques: Advancing high-school biology teachers' ability to ask research questions. Journal of Research in Science Teaching, 49(10), 1296-1320.

Hayenga, A. O., & Corpus, J. H. (2010). Profiles of intrinsic and extrinsic motivations: A person-centered approach to motivation and achievement in middle school. Motivation and Emotion, 34(4), 371-383.

Hektner, J. M., Schmidt, J. A., & Csikszentmihalyi, M. (2007). Experience sampling method: Measuring the quality of everyday life. Sage.

Jahnukainen, M. (2010). Extreme cases. Encyclopedia of Case Study Research. Thousand Oaks, CA: Sage. Konold, C., & Pollatsek, A. (2002). Data analysis as the search for signals in noisy processes. Journal for Research in Mathematics Education, 33(4), 259-289.

Lauer, P. A., Akiba, M., Wilkerson, S. B., Apthorp, H. S., Snow, D., & Martin-Glenn, M. L. (2006). Out-of-school-time programs: A meta-analysis of effects for at-risk students. Review of educational research, 76(2), 275-313.

Lee, H. S., Angotti, R. L., & Tarr, J. E. (2010). Making comparisons between observed data and expected outcomes: students' informal hypothesis testing with probability simulation tools. Statistics Education Research Journal, 9(1), 68-96.

Lee, H., & Hollebrands, K. (2008). Preparing to teach mathematics with technology: An integrated approach to developing technological pedagogical content knowledge. Contemporary Issues in Technology and Teacher Education, 8(4), 326-341.

Lehrer, R., & Romberg, T. (1996). Exploring children's data modeling. Cognition and Instruction, 14(1), 69-108.

Lehrer, R., & Schauble, L. (2004). Modeling natural variation through distribution. American Educational Research Journal, 41(3), 635-679.

Lehrer, R. & Schauble, L. (2015). Developing scientific thinking. In L. S. Liben & U. Müller (Eds.), Cognitive processes. Handbook of child psychology and developmental science (Vol. 2, 7th ed., pp. 671-174). Hoboken, NJ: Wiley.

Lehrer, R., Kim, M. J., & Jones, R. S. (2011). Developing conceptions of statistics by designing measures of distribution. ZDM, 43(5), 723-736.

Lehrer, R., Kim, M. J., & Schauble, L. (2007). Supporting the development of conceptions of statistics by engaging students in measuring and modeling variability. International Journal of Computers for Mathematical Learning, 12(3), 195-216.

Lesh, R., Middleton, J. A., Caylor, E., & Gupta, S. (2008). A science need: Designing tasks to engage students in modeling complex data. Educational Studies in Mathematics, 68(2), 113-130.

Linnansaari, J., Viljaranta, J., Lavonen, J., Schneider, B., & Salmela-Aro, K. (2015). Finnish Students Engagement in Science Lessons. NorDiNa: Nordic Studies in Science Education, 11(2), 192-206. Retrieved from https://www.journals.uio.no/index.php/nordina/article/view/2047

Lovett, M. C., & Shah, P. (2007). Preface. In M. C. Lovett & P. Shah (Eds.), Thinking with data (pp. x-xx [requested book through ILL to confirm page #s]). New York, NY: Lawrence Erlbaum.

Magnusson, D., & Cairns, R. B. (1996). Developmental science: Toward a unified framework. Cambridge, England: Cambridge University Press.

McNeill, K. L., & Berland, L. (2017). What is (or should be) scientific evidence use in k-12 classrooms? Journal of Research in Science Teaching, 54(5), 672-689.

Muthén, B. (2004). Latent variable analysis. The Sage handbook of quantitative methodology for the social sciences. Thousand Oaks, CA: Sage Publications, 345-68.

Muthén, L. K., & Muthén, B. O. (1998-2017). Mplus User's Guide. Los Angeles, CA: Muthén & Muthén. NGSS Lead States. (2013). Next generation science standards: For states, by states. Washington, DC: National Academies Press.

Nolen, S. B., Horn, I. S., & Ward, C. J. (2015). Situating motivation. Educational Psychologist, 50(3), 234-247. Patall, E. A., Vasquez, A. C., Steingut, R. R., Trimble, S. S., & Pituch, K. A. (2016). Daily interest, engagement, and autonomy support in the high school science classroom. Contemporary Educational Psychology, 46, 180-194.

Patall, E. A., Steingut, R. R., Vasquez, A. C., Trimble, S. S., Pituch, K. A., & Freeman, J. L. (2017). Daily Autonomy Supporting or Thwarting and Students' Motivation and Engagement in the High School Science Classroom. Journal of Educational Psychology. Advance online publication. http://dx.doi.org/10.1037/edu0000214

Pekrun, R., & Linnenbrink-Garcia, L. (2012). Academic emotions and student engagement. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), Handbook of research on student engagement (pp. 259-292). New York, NY: Springer. Petrosino, A., Lehrer, R., & Schauble, L. (2003). Structuring error and experimental variation as distribution in the fourth grade. Mathematical Thinking and Learning, 5 (2&3), 131-156.

Piaget, J., & Inhelder, B. (1969). The psychology of the child. New York, NY: Basic Books.

Pöysä, S., Vasalampi, K., Muotka, J., Lerkkanen, M. K., Poikkeus, A. M., & Nurmi, J. E. (2017). Variation in situation-specific engagement among lower secondary school students. Learning and Instruction. http://dx.doi.org/10.1016/j.learninstruc.2017.07.007

Rosenberg, J. M. (2018). Comparing mplus and mclust output. Retrieved from https://jrosen48.github.io/r-markdown/comparing-mplus-mclust.html Salmela-Aro, K., Moeller, J., Schneider, B., Spicer, J., & Lavonen, J. (2016). Integrating the light and dark sides of student engagement using person-oriented and situation-specific approaches. Learning and Instruction, 43, 61-70.

Salmela-Aro, K., Muotka, J., Alho, K., Hakkarainen, K., & Lonka, K. (2016). School burnout and engagement profiles among digital natives in Finland: A person-oriented approach. European Journal of Developmental Psychology, 13(6), 704-718.

Schneider, B., Krajcik, J., Lavonen, J., Salmela-Aro, K., Broda, M., Spicer, J., … & Viljaranta, J. (2016). Investigating optimal learning moments in US and Finnish science classes. Journal of Research in Science Teaching, 53(3), 400-421.

Schmidt, J. A., Rosenberg, J. M., Beymer, P. (advance online publication). A person-in-context approach to student engagement in science: Examining learning activities and choice. Journal of Research in Science Teaching. https://dx.doi.org/10.1002/tea.21409

Schwarz, N., Kahneman, D., & Xu, J. (2009). Global and episodic reports of hedonic experience. In R. Belli, D. Alwen, & F. Stafford (Eds.), Using calendar and diary methods in life events research (pp. 157-174). Newbury Park, CA: Sage.

Sfard, A. (1998). On two metaphors for learning and the dangers of choosing just one. Educational Researcher, 27(2), 4-13.

Shernoff, D. J., Csikszentmihalyi, M., Schneider, B., & Shernoff, E. S. (2003). Student engagement in high school classrooms from the perspective of flow theory. School Psychology Quarterly, 18(2), 158-176.

Shernoff, D. J., Kelly, S., Tonks, S. M., Anderson, B., Cavanagh, R. F., Sinha, S., & Abdi, B. (2016). Student engagement as a function of environmental complexity in high school classrooms. Learning and Instruction, 43, 52-60.

Shumow, L., & Schmidt, J. A. (2013). STEM interest and engagement (STEM I.E.). National Science Foundation proposal for award number 1421198.

Sinatra, G. M., Heddy, B. C., & Lombardi, D. (2015). The challenges of defining and measuring student engagement in science. Educational Psychologist, 50(1), 1-13. doi: 10.1080/00461520.2014.1002924

Singh, K., Granville, M., & Dika, S. (2002). Mathematics and science achievement: Effects of motivation, interest, and academic engagement. The Journal of Educational Research, 95(6), 323-332. Shernoff, D. J., & Schmidt, J. A. (2008). Further Evidence of an Engagement–Achievement Paradox Among U.S. High School Students. Journal of Youth and Adolescence, 37(5), 564–580. http://doi.org/10.1007/s10964-007-9241-z

Shumow, L., Schmidt, J. A., & Zaleski, D. J. (2013). Multiple perspectives on student learning, engagement, and motivation in high school biology labs. The High School Journal, 96(3), 232-252.

Skinner, E. A., & Pitzer, J. (2012). Developmental dynamics of engagement, coping, and everyday resilience. In S. Christenson, A. Reschly, & C. Wylie (Eds.), Handbook of Research on Student Engagement (pp. 21-45). New York: Springer Science.

Skinner, E. A., Kindermann, T. A., & Furrer, C. J. (2009). A motivational perspective on engagement and disaffection: Conceptualization and assessment of children's behavioral and emotional participation in academic activities in the classroom. Educational and Psychological Measurement, 69(3), 493-525.

Skinner, E., Furrer, C., Marchand, G., & Kindermann, T. (2008). Engagement and disaffection in the classroom: Part of a larger motivational dynamic? Journal of Educational Psychology, 100(4), 765.

Smith, C., Akiva, T., Sugar, S., Lo, Y. J., Frank, K. A., Peck, S. C., Cortina, K. S., & Devaney, T. (2012).Continuous quality improvement in afterschool settings: Impact findings from the Youth Program Quality Intervention study. Washington, DC: The Forum for Youth Investment. Steinley, D., & Brusco, M. J. (2011). Evaluating mixture modeling for clustering: recommendations and cautions. Psychological Methods, 16(1), 63.

Stohl, H., & Tarr, J. E. (2002). Developing notions of inference using probability simulation tools. The Journal of Mathematical Behavior, 21(3), 319-337.

Stroupe, D. (2014). Examining classroom science practice communities: How teachers and students negotiate epistemic agency and learn science-as-practice. Science Education, 98(3), 487-516.

Strati, A. D., Schmidt, J. A., & Maier, K. S. (2017). Perceived challenge, teacher support, and teacher obstruction as predictors of student engagement. Journal of Educational Psychology, 109(1), 131-147.

Trevors, G. J., Kendeou, P., Bråten, I., & Braasch, J. L. (2017). Adolescents' epistemic profiles in the service of knowledge revision. Contemporary Educational Psychology, 49, 107-120.

Turner, J. C., & Meyer, D. K. (2000). Studying and understanding the instructional contexts of classrooms: Using our past to forge our future. Educational Psychologist, 35(2), 69-85.

van Rooij, E. C., Jansen, E. P., & van de Grift, W. J. (2017). Secondary school students' engagement profiles and their relationship with academic adjustment and achievement in university. Learning and Individual Differences, 54, 9-19.

Vandell, D. L., Hall, V., O'Cadiz, P., & Karsh, A. (2012). Piloting outcome measures for summer learning initiative programs. Final report to the David and Lucile Packard Foundation, Children, Families, and Communities Program. Retrieved from http://faculty.sites.uci.edu/childcare/files/2013/07/SL-Outcomes-2011-Pilot_Edited_8.19.pdf

Wang, M. T., & Eccles, J. S. (2012). Social support matters: Longitudinal effects of social support on three dimensions of school engagement from middle to high school. Child Development, 83(3), 877-895.

Wang, M. T., & Holcombe, R. (2010). Adolescents' perceptions of school environment, engagement, and academic achievement in middle school. American Educational Research Journal, 47(3), 633-662.

Westfall, J., Kenny, D. A., & Judd, C. M. (2014). Statistical power and optimal design in experiments in which samples of participants respond to samples of stimuli. Journal of Experimental Psychology: General, 143(5), 2020-2045.

Westfall, J. (2016). PANGEA: Power Analysis for General Anova designs. Retrieved from https://jakewestfall.shinyapps.io/pangea/

Wickham, H. (2018). CRAN downloads. Retrieved from https://hadley.shinyapps.io/cran-downloads/ Wild, C. J., & Pfannkuch, M. (1999). Statistical thinking in empirical enquiry. International Statistical Review, 67(3), 223-248.

Wilkerson, M. H., Andrews, C., Shaban, Y., Laina, V., & Gravel, B. E. (2016). What's the technology for? Teacher attention and pedagogical goals in a modeling-focused professional development workshop. Journal of Science Teacher Education, 27(1), 11-33.

Wilkerson, M. H. & Fenwick, M. (2017). The practice of using mathematics and computational thinking. In C. V. Schwarz, C. Passmore, & B. J. Reiser (Eds.), Helping Students Make Sense of the World Using Next Generation Science and Engineering Practices. Arlington, VA: National Science Teachers' Association Press. pp. 181-204.

Witherington, D. C. (2015). Dynamic systems in developmental science. In W. F. Overton & P. C. M. Molenaar (Vol. Eds.) & R. M. Lerner (Ed.), Handbook of child psychology and developmental science. Vol. 1: Theory & method (7th ed., pp. 63-112). Hoboken, NJ: Wiley.

Wormington, S. V., & Linnenbrink-Garcia, L. (advance online publication). A new look at multiple goal pursuit: The promise of a person-centered approach. Educational Psychology Review. doi:10.1007/s10648-016-9358-2

Chapter 11

Appendix

11.1 Appendix: STEM-PQA alignment

```
## Error: <text>:2:200: unexpected symbol
## 1: tibble::tribble(
## 2:   ~Work.With.Data.Codes.Originally.Proposed,
##
```

11.2 Appendix: Method additional materials

11.2.1 Statistical software developed

The functions in tidyLPA dynamically generate MPlus syntax, so that, for example, a user can simply provide a data frame with variables to be used in the analysis, the specification for one of six models, the number of profiles to be estimated as part of the analysis, and a number of fine-grained options concerning the estimation and the output generated. From these inputs, a data file for MPlus is prepared and saved, the model syntax is created and saved in a model input file, the model is run, and the output, including the "savedata", or the data with its associated posterior probabilities and profile assignments, is returned to R for use plots or in subsequent analyses.

Because of the considerable time that it takes to generate MPlus model syntax (i.e., when choosing to specify a model with different parameters or when changing the number of profiles to be estimated as part of the solution), this package makes it easier to carry out LPA in a flexible way, while retaining the power of the MPlus software. While this functionality makes it considerably easier to carry out LPA, it requires that MPlus be purchased and installed. Because of this, the R package I developed also includes wrapper functions to an open-source tool, mclust (Scrucca, Fop, Murphy, & Raftery, 2016). This is a very widely-used package for mixture modeling. While some authors have suggested that it can be used to carry out LPA (Oberski, 2016), a key challenge for analysts using it concerns specifying the models. This is because the models are described in terms of the geometric properties of the multivariate distributions being estimated (i.e., "spherical, equal volume"), rather than in terms of whether and how the means, variances, and covariances are estimated. This R package corresponds LPA models to the mclust models and provides the same functionality that the functions that use MPlus provide, namely, preparing data, running the model, and returning the output or use in subsequent analyses. As part of incorporating the mclust functionality, the functions that use MPlus and those that use mclust have been benchmarked (Rosenberg, 2018). Despite leading to identical results (in most cases) for small datasets, because of differences in how the E-M algorithm

Table 11.1: Correlations among codes for instructional support for work with data (and composite of all codes)

rowname	Asking.Questions	Making.Observations	Generating.Data	Data.Modeling	Communicatin
Asking Questions		.38	.28	.43	.73
Making Observations	.38		.24	.18	.55
Generating Data	.28	.24		.30	.65
Data Modeling	.43	.18	.30		.67
Communicating Findings	.73	.55	.65	.67	

is initialized as well as other estimation-related differences, output will likely not be identical for many analyses.

11.2.2 Appendix: Descriptive statistics additional materials

The Spearman rank (because the data were dichotomous) correlations among the aspects of instructional support for work with data are presented. The variables were moderately correlated, with *rho* values between .18 and .50. These suggest that signals are assocaited

11.2.3 Appendix: Program descriptions

Table 11.2: STEM Enrichment Program Names and Their 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 writ
The Ecosphere	A science-focused program that aims to help youth to explore the marine life of Narragansett Bay. Efforts were undertaken to build y
Zoology Partners	A science-focused program that aims to support youth's development of content knowledge related to the issue of endangered species
Marine Investigators	A science-focused program that aims to provide youth with opportunities to learn about and experience Narragansett Bay; examine
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
Jefferson House	A STEM-focused program that aims to support youth's development of basic math skills, the program was primarily focused on help
Uptown Architecture	An engineering-focused program that aims to support youth's participation in a process to design and build an outdoor learning spac
Building Mania	An engineering-focused program that aims to provide youth with the opportunity to experiment with designing and using simple mac
Adventures in Mathematics	A mathematics-focused program that aims to help youth to develop the basic math skills and prevent summer learning loss among pa

11.2.4 Appendix: Research Question #1 additional materials

11.2.5 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).

11.2.5.1 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).

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

11.2.5.2 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).

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

11.2.5.3 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.

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

11.2.5.4 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.

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

11.2.5.5 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.

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

11.2.5.6 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.

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

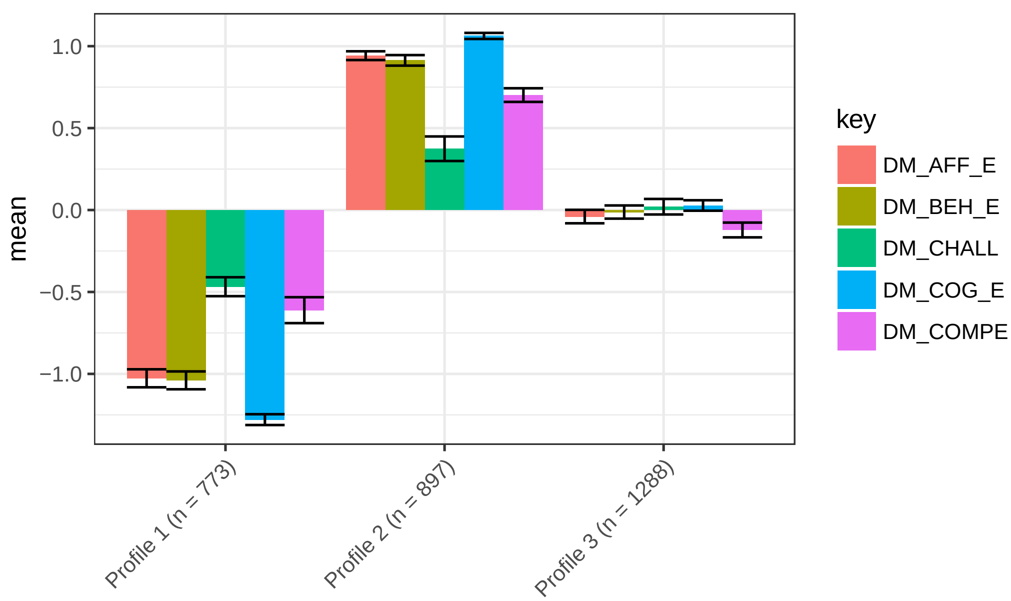
11.2.6 Model 1 candidate solutions

11.2.6.1 Model: 1, Profiles: 3

This solution is characterized by:

- a **full** profile, profile 2 (though with more modestly high levels of challenge)
- a **universally low** profile, profile 1 (again with more modestly - in this case low - levels of challenge)
- an **all moderate** profile, profile 3, characterized by levels of all of the variables close to the mean, profile 3

The number of observations associated with each of the profiles is somewhat balanced, with the all moderate profile demonstrating a higher number of observations (n = 1,288) than the full (n = 897) and universally low (n = 773) profiles. The log-likelihood was replicated many (more than 10) times. Because the profiles associated with this solution all demonstrated the same overall pattern (i.e., all five variables are high, low, or moderate), on the basis of interpretability, this particular solution may not be useful in terms of understanding how youth experience engagement and its conditions.



11.2.6.2 Model: 1, Profiles: 4

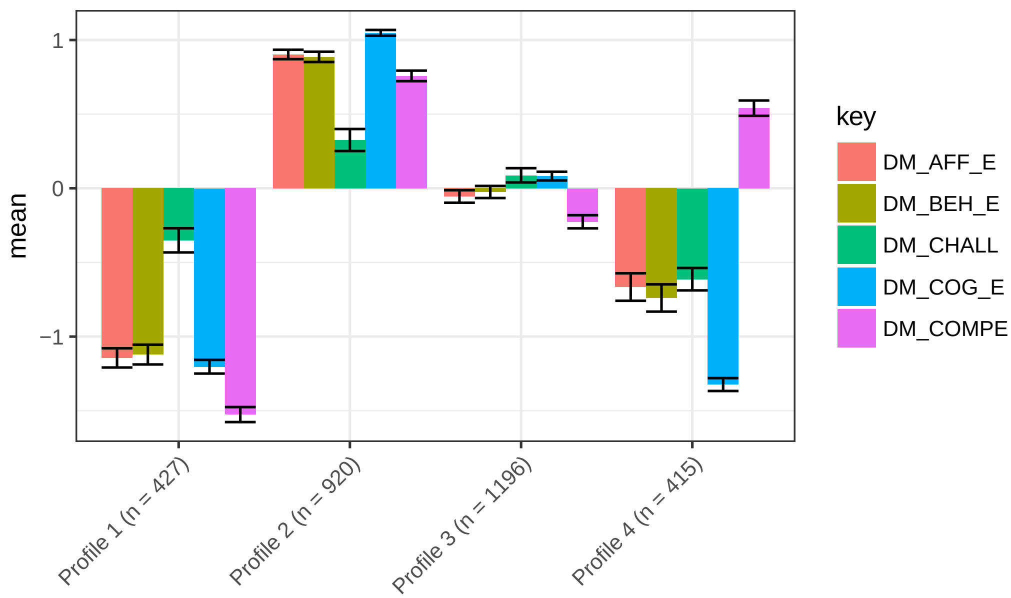
This solution is characterized by:

- a **full** profile, profile 2

- a **universally low** profile, profile 1
- an **all moderate** profile, profile 3.
- a **competent but not engaged or challenged** profile, with high levels of competence and low levels of engagement and challenge

Most profiles are in the all moderate profile (n = 1,288), with a large number in the full (n = 920) profile, and fewer in the universally low and competent (n n = 427) but not engaged or challenged profiles (n = 415). With somewhat more purchase in terms of its interpretability than the solution for model 1 with three profiles, like that solution, this one may not be as useful as more complex models for understanding youth's experiences.

The log-likelihood was replicated many (more than 10) times.

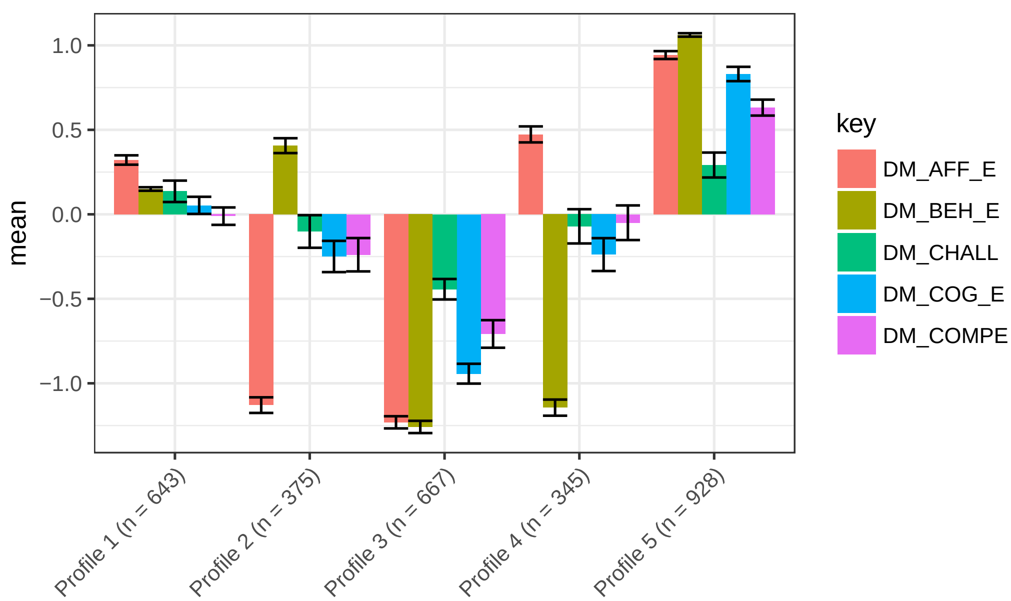


11.2.6.3 Model: 1, Profiles: 5

This solution is characterized by:

- a **full** profile, profile 5
- a **universally low** profile, profile 3
- an **all moderate** profile, profile 3, though with moderate levels of affective engagement than in similar profiles associated with the four and five profile solutions, perhaps suggesting that a different profile than in those solutions
- an **only behavioral** profile, profile 2, with moderate levels of behavioral engagement, very low affective engagement, and moderately (low) levels of cognitive engagement and challenge and competence
- an **only affective** profile, profile 4, with moderate levels of affective engagement, low levels of behavioral engagement, and moderately (low) levels of cognitive engagement and challenge and competence

The number of observations associated with each of the profiles is somewhat balanced, with a large number in the full profile (n = 928), a moderate number of observations in the universally low (n = 667) and all moderate (n = 643) profiles, and fewer observations in the only behaviorally engaged (n = 375) and only affective engaged (n = 345) profiles. This solution primarily distinguishes between affective and behavioral engagement; unlike the solution for model 1 with four profiles, there is not a competent but not engaged or challenged profile. This may suggest that solutions with a greater number of profiles represents both the distinction between behavioral and affective engagement highlighted by profiles in this solution as well as profiles that are characterized by higher or lower levels of the conditions for engagement (i.e., competence). The log-likelihood was replicated four times.

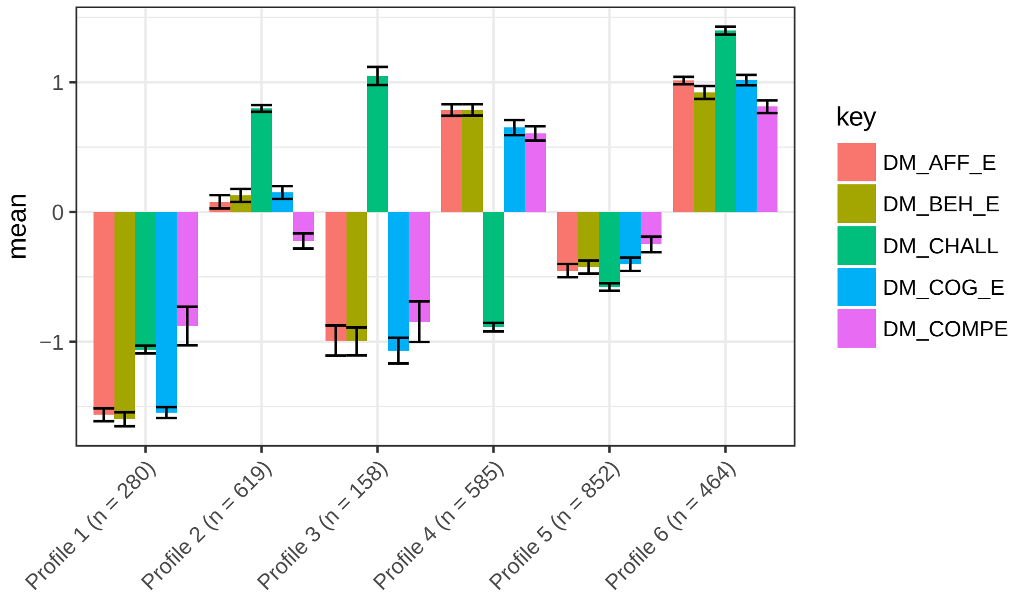


11.2.6.4 Model: 1, Profiles: 6 (alternate)

This solution is characterized by:

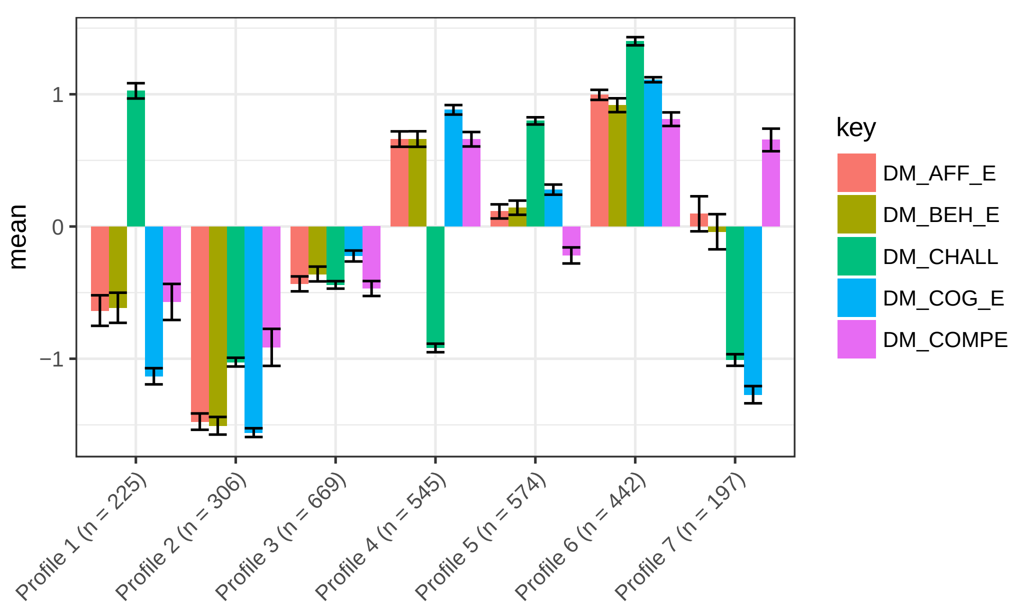
- a **full** profile, profile 6
- a **universally low** profile, profile 1
- an **engaged and competent but not challenged** profile, profile 3
- a **challenged** profile, profile 2
- a **highly challenged** profile, profile 3
- a **moderately low** profile, profile 5

The number of observations are not very balanced, with the moderately low profile with a large number of observations ($n = 852$) and the challenged, engaged and competent but not challenged, and full profiles with moderate numbers of observations (from 464 to 619 observations), and low numbers of observations exhibited by universally low ($n = 280$) and highly challenged ($n = 158$) profiles. This–and, critically, the lower log-likelihood of the other model 1, six profile solution–suggests that this solution is not preferred. However, the very different profiles that emerge for this solution suggest that there might not be a somewhat under-identified solution associated with model 1 and six profiles.



11.2.6.5 Model: 1, Profiles: 7 (alternate)

When investigating an alternate solution (associated with the second lowest log-likelihood) for the model 1, seven profile solution, we can see that even for the solutions associated with other log-likelihoods, the profiles that can be identified are very similar. One minor distinction concerns the **competent but not engaged or challenged** profile, which in the alternate solution is associated with neutral levels of affective engagement, compared to moderately low levels of affective engagement in the solution with the lowest log-likelihood. Because five of the seven profiles associated with both of these model 1, seven profile solutions seem to be distinct from those identified from simpler model 1 solutions, investigation of this alternate solution provides additional evidence that these profiles are not associated with an under-identified model and that simpler models may be preferred over these seven profile solutions.



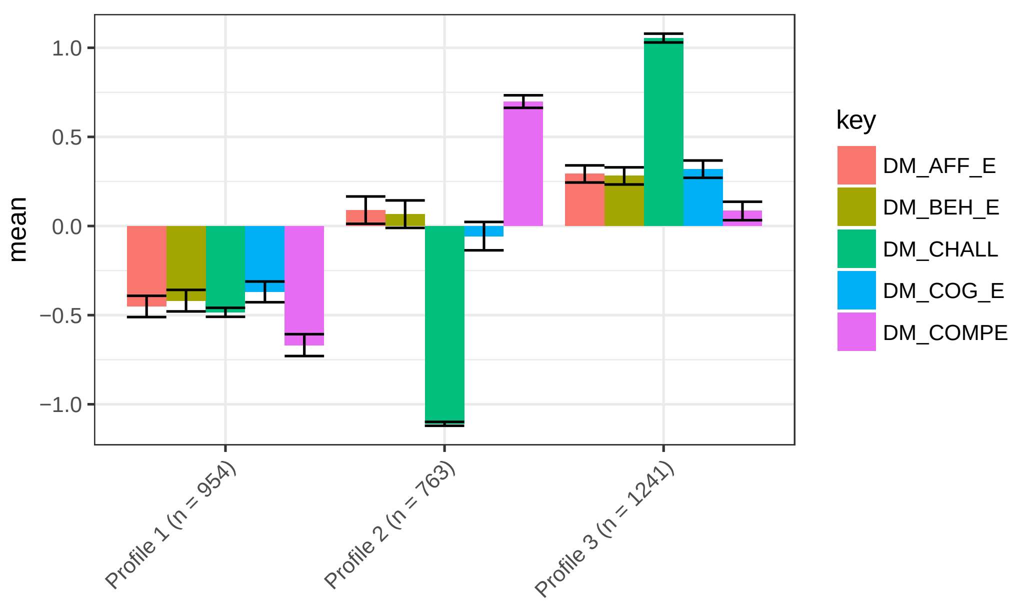
11.2.7 Model 2 candidate solutions

11.2.7.1 Model: 2, Profiles: 3

This solution is characterized by:

- a **universally low** profile, profile 1, associated with moderate (low) and low levels of all of the variables; this profile is similar to the universally low profile identified as part of other solutions, although with more moderate values for some of the variables (especially cognitive engagement)
- a **competent but not challenged** profile, profile 2, characterized by high competence and low challenge
- a **challenged** profile, profile 3, characterized by very high challenge and moderate (high) levels of the other variables, similar to the challenged profile found as part of the model 1, four profile solution, but with higher levels of competence, which are moderately high in this solution but moderately low for the other solution.

The number of observations associated with each solution is fairly balanced, with the most in the challenged profile (n = 1,241), followed by the universally low (n = 954 observations) and competent but not challenged (n = 763) profiles. This solution is very different than the three profile solution that was interpreted for model 1. Model 2 differs from model 1 in that covariances between the variables are estimated (they are constrained to be the same are across the profiles). The log-likelihood was replicated (at least) ten times. Thus, this and other solutions associated with model 2 include information about how the variables relate. Including this information seems to be associated with profiles that differentiate the groups on the basis of the levels of each of the variables in more distinct ways: the model 1, three profile solution was characterized by high, moderate, or low levels of all variables for each of the three profiles.



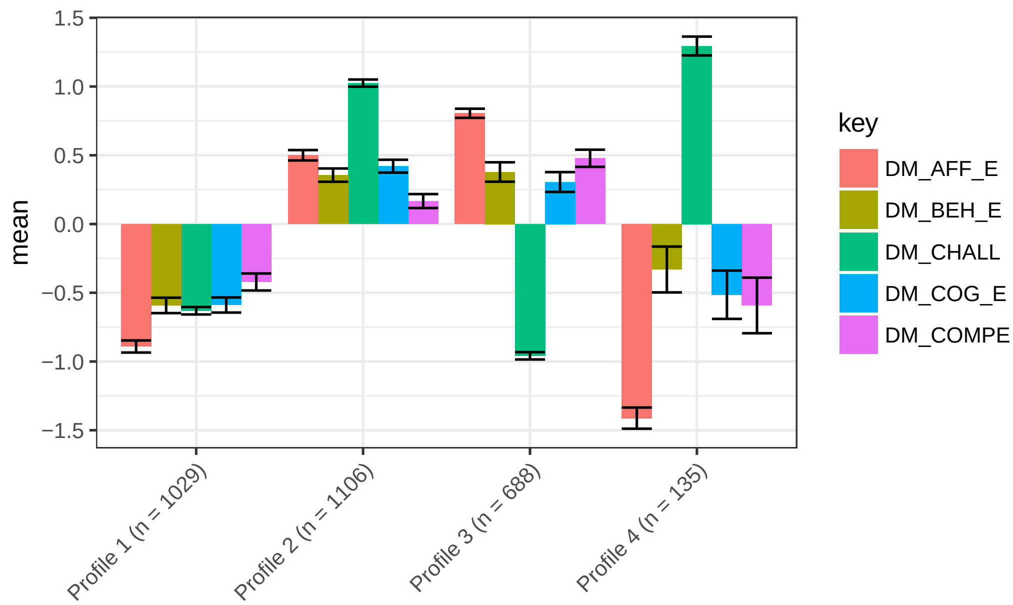
11.2.7.2 Model: 2, Profiles: 4

This solution is characterized by:

- a **universally low** profile, profile 1
- a **challenged** profile, profile 2

- a **highly challenged** profile, profile 4
- an **engaged and competent but not challenged** profile, profile 3

The number of observations in each of the profiles is not very balanced, with more than 1,000 observations in both the universally low (n = 1,029) and challenged (n = 1,106) profiles, a moderate number if the engaged and competent but not challenged profile (n = 688), and very few in the highly challenged (n = 135) profile. The log-likelihood was replicated three times. While each of these profiles has been identified in another solution, the small number of observations in the highly challenged profile suggests that this solution be interpreted with some skepticism because of the potentially limited utility (and statistical power associated with the use) of the profiles in subsequent analyses.

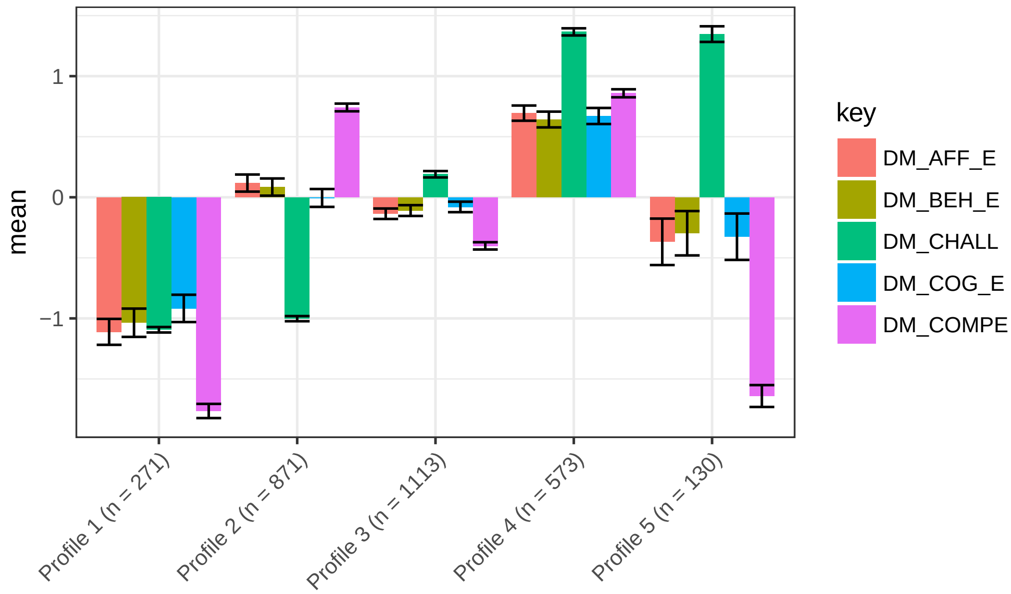


11.2.7.3 Model: 2, Profiles: 5

This solution is characterized by:

- a **universally low** profile, profile 1
- a **full** profile, profile 4, although with very high levels of challenged (in addition to high levels of all of the other variables), making this profile similar to that (challenged) profile
- a **highly challenged** profile, profile 5
- an **all moderate** profile, profile 3, although with moderately lower levels of competence than is found in profiles associated with other solutions
- a **competent but not challenged** profile, profile 2, similar to the competent but not challenged or engaged profile, but with neutral, rather than low, levels of the engagement variables

The number of observations associated with each of the profiles is not very balanced, with a very large number of observations in the all moderate profile (n = 1,113) and a large number in the competent but not challenged profile (n = 871), a moderate number in the full profile (n = 573), and very few in the universally low (n = 271) and challenged but not competent (n = 130) profiles. The log-likelihood was replicated four times. Like for the model 2, four profile solution, the small number of observations associated with two of the profiles suggests that this solution should be interpreted with some caution.



11.3 Appendix: Models for research question #2 and #3 with the seven-profile solution

Table 11.3: Results of mixed effects models for instructional support for work with data as separate variables

model	intercept	dm_ask	dm_obs	dm_gen	dm_mod	dm_com	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.072 (0.01) (p < .001)	-0.011 (0.011) (p = 0.839)	0.001 (0.011) (p = 0.457)	-0.005 (0.01) (p = 0.686)	-0.002 (0.011) (p = 0.58)	-0.002 (0.01) (p = 0.583)	0.008	0.176	0.002
Competent but not engaged or challenged	0.111 (0.019) (p < .001)	0.002 (0.013) (p = 0.428)	-0.007 (0.013) (p = 0.696)	-0.01 (0.012) (p = 0.78)	-0.025 (0.014) (p = 0.969)	-0.002 (0.013) (p = 0.549)	0.014	0.222	0.021
Moderately low	0.186 (0.029) (p < .001)	0.024 (0.017) (p = 0.077)	0.024 (0.017) (p = 0.074)	0.009 (0.016) (p = 0.281)	-0.002 (0.018) (p = 0.544)	0.027 (0.017) (p = 0.053)	0.016	0.279	0.033
Challenged	0.197 (0.023) (p < .001)	0.011 (0.016) (p = 0.252)	-0.013 (0.016) (p = 0.799)	0.034 (0.015) (p = 0.015)	-0.005 (0.017) (p = 0.626)	-0.002 (0.016) (p = 0.561)	0.007	0.261	0.015
Highly challenged	0.083 (0.01) (p < .001)	-0.007 (0.012) (p = 0.714)	0 (0.012) (p = 0.504)	-0.016 (0.012) (p = 0.913)	0.017 (0.013) (p = 0.1)	-0.013 (0.012) (p = 0.859)	0.023	0.104	0.000
Engaged and competent but not challenged	0.199 (0.018) (p < .001)	-0.014 (0.017) (p = 0.787)	0.019 (0.017) (p = 0.129)	-0.033 (0.016) (p = 0.979)	-0.013 (0.018) (p = 0.77)	0.019 (0.017) (p = 0.127)	0.015	0.286	0.000
Full	0.154 (0.023) (p < .001)	-0.009 (0.014) (p = 0.748)	-0.024 (0.014) (p = 0.961)	0.022 (0.013) (p = 0.048)	0.032 (0.014) (p = 0.012)	-0.025 (0.013) (p = 0.97)	0.018	0.513	0.012

Table 11.4: Results of mixed effects models for the composite

model	intercept	dm_composite	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.071 (0.01) (p < .001)	-0.004 (0.003) (p = 0.937)	0.007	0.176	0.002
Competent but not engaged or challenged	0.113 (0.019) (p < .001)	-0.008 (0.003) (p = 0.993)	0.013	0.222	0.022
Moderately low	0.188 (0.029) (p < .001)	0.016 (0.004) (p < .001)	0.015	0.279	0.032
Challenged	0.2 (0.023) (p < .001)	0.005 (0.004) (p = 0.09)	0.007	0.260	0.015
Highly challenged	0.08 (0.01) (p < .001)	-0.004 (0.003) (p = 0.917)	0.022	0.104	0.000
Engaged and competent but not challenged	0.2 (0.018) (p < .001)	-0.005 (0.004) (p = 0.887)	0.015	0.285	0.000
Full	0.151 (0.023) (p < .001)	0 (0.003) (p = 0.527)	0.019	0.510	0.013

Table 11.5: Results of mixed effects models for the composite

model	intercept	dm_composite_di	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.078 (0.012) (p < .001)	-0.02 (0.01) (p = 0.98)	0.006	0.176	0.003
Competent but not engaged or challenged	0.118 (0.019) (p < .001)	-0.03 (0.012) (p = 0.993)	0.014	0.223	0.021
Moderately low	0.175 (0.029) (p < .001)	0.063 (0.016) (p < .001)	0.015	0.279	0.031
Challenged	0.203 (0.024) (p < .001)	0.01 (0.015) (p = 0.261)	0.008	0.260	0.014
Highly challenged	0.083 (0.011) (p < .001)	-0.016 (0.011) (p = 0.922)	0.023	0.104	0.000
Engaged and competent but not challenged	0.198 (0.019) (p < .001)	-0.011 (0.016) (p = 0.763)	0.015	0.285	0.000
Full	0.146 (0.024) (p < .001)	0.006 (0.013) (p = 0.308)	0.019	0.510	0.014

Table 11.6: Results of mixed effects models with interest and other characteristics

model	intercept	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.069 (0.04) ($p = 0.042$)	-0.002 (0.01) ($p = 0.569$)	0.017 (0.018) ($p = 0.177$)	-0.005 (0.025) ($p = 0.576$)	0.016	0.194	0.000
Competent but not engaged or challenged	0.126 (0.049) ($p = 0.006$)	-0.011 (0.013) ($p = 0.808$)	0.021 (0.022) ($p = 0.165$)	-0.007 (0.031) ($p = 0.591$)	0.017	0.211	0.003
Moderately low	0.301 (0.082) ($p < .001$)	-0.023 (0.021) ($p = 0.869$)	0.02 (0.034) ($p = 0.275$)	-0.018 (0.048) ($p = 0.642$)	0.017	0.290	0.030
Challenged	0.297 (0.073) ($p < .001$)	-0.013 (0.019) ($p = 0.757$)	-0.04 (0.031) ($p = 0.9$)	-0.032 (0.044) ($p = 0.768$)	0.013	0.254	0.016
Highly challenged	0.108 (0.034) ($p = 0.001$)	-0.014 (0.009) ($p = 0.946$)	-0.013 (0.015) ($p = 0.803$)	0.016 (0.021) ($p = 0.221$)	0.026	0.112	0.001
Engaged and competent but not challenged	0.065 (0.07) ($p = 0.177$)	0.033 (0.018) ($p = 0.034$)	0.042 (0.032) ($p = 0.094$)	-0.002 (0.045) ($p = 0.518$)	0.013	0.275	0.000
Full	0.048 (0.082) ($p = 0.28$)	0.022 (0.021) ($p = 0.142$)	-0.043 (0.037) ($p = 0.878$)	0.06 (0.053) ($p = 0.129$)	0.023	0.510	0.000

Table 11.7: Results of mixed effects models with interest and other characteristics and the aspects of work with data

model	intercept	dm_ask	dm_obs	dm_gen	dm_mod	dm_com	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.077 (0.041) (p = 0.031)	-0.01 (0.011) (p = 0.822)	0.002 (0.011) (p = 0.429)	-0.003 (0.011) (p = 0.612)	-0.003 (0.012) (p = 0.616)	-0.002 (0.011) (p = 0.569)	-0.003 (0.01) (p = 0.63)	0.017 (0.018) (p = 0.166)	-0.002 (0.025) (p = 0.535)	0.008	0.189	0.004
Competent but not engaged or challenged	0.141 (0.05) (p = 0.003)	0.002 (0.013) (p = 0.432)	-0.011 (0.013) (p = 0.803)	-0.007 (0.013) (p = 0.718)	-0.028 (0.014) (p = 0.978)	0.003 (0.013) (p = 0.421)	-0.013 (0.013) (p = 0.839)	0.021 (0.022) (p = 0.167)	-0.011 (0.03) (p = 0.644)	0.013	0.201	0.011
Moderately low	0.271 (0.084) (p < .001)	0.024 (0.018) (p = 0.087)	0.027 (0.017) (p = 0.061)	0.002 (0.017) (p = 0.447)	0 (0.018) (p = 0.499)	0.033 (0.017) (p = 0.03)	-0.024 (0.021) (p = 0.869)	0.02 (0.034) (p = 0.284)	-0.019 (0.049) (p = 0.649)	0.014	0.288	0.036
Challenged	0.279 (0.075) (p < .001)	0.018 (0.017) (p = 0.138)	-0.003 (0.017) (p = 0.568)	0.029 (0.016) (p = 0.036)	-0.005 (0.017) (p = 0.606)	-0.006 (0.017) (p = 0.648)	-0.011 (0.019) (p = 0.725)	-0.042 (0.032) (p = 0.906)	-0.032 (0.045) (p = 0.762)	0.007	0.253	0.022
Highly challenged	0.128 (0.035) (p < .001)	-0.004 (0.013) (p = 0.63)	-0.008 (0.013) (p = 0.722)	-0.016 (0.012) (p = 0.9)	0.023 (0.014) (p = 0.048)	-0.022 (0.013) (p = 0.951)	-0.015 (0.009) (p = 0.959)	-0.009 (0.015) (p = 0.721)	0.013 (0.021) (p = 0.263)	0.025	0.108	0.000
Engaged and competent but not challenged	0.071 (0.071) (p = 0.161)	-0.018 (0.017) (p = 0.854)	0.017 (0.017) (p = 0.164)	-0.027 (0.016) (p = 0.948)	-0.013 (0.018) (p = 0.759)	0.017 (0.017) (p = 0.168)	0.034 (0.018) (p = 0.034)	0.046 (0.032) (p = 0.079)	-0.001 (0.045) (p = 0.509)	0.013	0.279	0.000
Full	0.053 (0.085) (p = 0.266)	-0.015 (0.014) (p = 0.852)	-0.026 (0.014) (p = 0.967)	0.022 (0.013) (p = 0.048)	0.029 (0.015) (p = 0.026)	-0.022 (0.014) (p = 0.938)	0.023 (0.021) (p = 0.148)	-0.043 (0.038) (p = 0.868)	0.063 (0.055) (p = 0.127)	0.021	0.534	0.000

Table 11.8: Results of mixed effects models with interest and other characteristics and the composite work with data

model	intercept	dm_composite	overall_pre_interest	gender_female	urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.077 (0.041) (p = 0.031)	-0.004 (0.003) (p = 0.908)	-0.004 (0.01) (p = 0.632)	0.017 (0.018) (p = 0.168)	-0.002 (0.025) (p = 0.533)	0.007	0.189	0.004
Competent but not engaged or challenged	0.144 (0.05) (p = 0.002)	-0.008 (0.003) (p = 0.992)	-0.013 (0.013) (p = 0.841)	0.022 (0.022) (p = 0.159)	-0.012 (0.03) (p = 0.65)	0.012	0.201	0.012
Moderately low	0.273 (0.083) (p < .001)	0.017 (0.004) (p < .001)	-0.024 (0.021) (p = 0.871)	0.02 (0.034) (p = 0.278)	-0.019 (0.049) (p = 0.653)	0.013	0.288	0.034
Challenged	0.28 (0.075) (p < .001)	0.007 (0.004) (p = 0.044)	-0.011 (0.019) (p = 0.717)	-0.042 (0.032) (p = 0.905)	-0.032 (0.045) (p = 0.763)	0.006	0.253	0.022
Highly challenged	0.125 (0.035) (p < .001)	-0.005 (0.003) (p = 0.951)	-0.016 (0.009) (p = 0.964)	-0.01 (0.015) (p = 0.733)	0.014 (0.021) (p = 0.254)	0.024	0.109	0.000
Engaged and competent but not challenged	0.072 (0.071) (p = 0.156)	-0.006 (0.004) (p = 0.911)	0.033 (0.018) (p = 0.035)	0.046 (0.032) (p = 0.078)	0 (0.045) (p = 0.503)	0.012	0.279	0.000
Full	0.05 (0.085) (p = 0.278)	-0.001 (0.004) (p = 0.657)	0.023 (0.021) (p = 0.143)	-0.045 (0.038) (p = 0.878)	0.063 (0.055) (p = 0.126)	0.022	0.532	0.000

Table 11.9: Results of mixed effects models with the interactions between interest and other characactistics and the composite for work with data

model	intercept	dm_composite	overall_pre_interest	gender_female	urm	overall_pre_interest:dm_composite	dm_composite:gender_female	dm_composite:urm	beep_ID_ICC	participant_ID_ICC	program_ID_ICC
Universally low	0.113 (0.046) (p = 0.008)	-0.022 (0.012) (p = 0.973)	-0.014 (0.012) (p = 0.878)	0.025 (0.021) (p = 0.113)	-0.012 (0.029) (p = 0.663)	0.005 (0.003) (p = 0.038)	-0.004 (0.005) (p = 0.761)	0.005 (0.007) (p = 0.225)	0.007	0.189	0.004
Competent but not engaged or challenged	0.133 (0.056) (p = 0.009)	-0.002 (0.013) (p = 0.553)	-0.01 (0.015) (p = 0.761)	0.031 (0.025) (p = 0.106)	-0.013 (0.035) (p = 0.643)	-0.001 (0.003) (p = 0.656)	-0.005 (0.006) (p = 0.784)	0.001 (0.008) (p = 0.466)	0.012	0.201	0.011
Moderately low	0.256 (0.089) (p = 0.002)	0.026 (0.017) (p = 0.071)	-0.017 (0.023) (p = 0.774)	0.015 (0.038) (p = 0.345)	-0.02 (0.053) (p = 0.643)	-0.003 (0.005) (p = 0.767)	0.003 (0.008) (p = 0.376)	0 (0.011) (p = 0.505)	0.013	0.287	0.034
Challenged	0.262 (0.082) (p < .001)	0.016 (0.017) (p = 0.178)	-0.002 (0.021) (p = 0.542)	-0.063 (0.035) (p = 0.961)	-0.03 (0.05) (p = 0.724)	-0.004 (0.005) (p = 0.83)	0.011 (0.008) (p = 0.094)	-0.002 (0.011) (p = 0.573)	0.006	0.253	0.022
Highly challenged	0.12 (0.042) (p = 0.002)	-0.003 (0.013) (p = 0.608)	-0.018 (0.011) (p = 0.951)	-0.015 (0.019) (p = 0.778)	0.03 (0.026) (p = 0.126)	0.001 (0.003) (p = 0.368)	0.003 (0.006) (p = 0.317)	-0.008 (0.008) (p = 0.851)	0.025	0.108	0.000
Engaged and competent but not challenged	0.07 (0.078) (p = 0.185)	-0.004 (0.017) (p = 0.593)	0.029 (0.02) (p = 0.079)	0.065 (0.036) (p = 0.034)	0.007 (0.05) (p = 0.441)	0.002 (0.005) (p = 0.319)	-0.01 (0.008) (p = 0.888)	-0.003 (0.011) (p = 0.624)	0.012	0.277	0.000
Full	0.073 (0.088) (p = 0.205)	-0.014 (0.013) (p = 0.848)	0.021 (0.022) (p = 0.172)	-0.057 (0.04) (p = 0.921)	0.049 (0.057) (p = 0.196)	0.001 (0.003) (p = 0.38)	0.006 (0.006) (p = 0.148)	0.007 (0.008) (p = 0.202)	0.022	0.532	0.000