Examining Work With Data in STEM Education Through the Lens of Engagement Theory: A Person-Oriented Approach Using an Experience Sampling Method

Joshua M. Rosenberg

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Chapter 1

Front Matter

1.0.1 Dedication

This dissertation is dedicated to Katie.

1.0.2 Acknowledgments

First, I would like to acknowledge my advisor and dissertation co-director Matthew Koehler and my dissertation co-director Jennifer Schmidt.

1.0.3 Abstract

This study will examine how 203 early adolescent learners work with data, or engage in activities focused on constructing measures of and modeling data, in the context of STEM summer enrichment programs. Video recordings of programs will be coded to identify the presence of five aspects of learners' work with data: asking questions or identifying problems, constructing measures, collecting data, accounting for variability or uncertainty, and interpreting and communicating findings. Additionally, measures of instructional support for such practices will be used, so codes for work with data with instructional support are also created. Youth's responses to the Experience Sampling Method (ESM) will be used to examine their cognitive, behavioral, and affective engagement as well as their perceptions of challenge and competence. A person-oriented analytic approach will be used to identify profiles of engagement that will help us to understand how learners engage in work with data. Examining work with data in terms of contemporary engagement theory can help us to understand these key STEM activities in terms of learner's experience, which past research suggests impacts student learning, yet which has not been brought to bear on the topic of work with data. Knowing more about students' engagement can help us to design activities and interventions around work with data that are highly engaging to students and that support their capabilities to work with data.

Chapter 2

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 3

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.

3.1 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., 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.

Figure 1. Work with data in STEM education settings.

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.

3.2 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).

3.3 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.

3.4 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.

3.5 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.

3.6 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.

3.7 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.

Figure 2. A conceptual framework for this study with research questions labeled.

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.

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).

3.8 Research Questions

The four research questions are as follows: 1. What profiles of engagement and its conditions (PECs) emerge from the participants' responses? 2. How does work with data relate to each PEC? a. How does work with data, in general, relate to PEC? b. How do the specific aspects of work with data (i.e., asking questions or identifying problems, constructing measures, accounting for variability or uncertainty, and interpreting and communicating findings), and other activities that are not work with data, relate to each PEC? 3. How do the relationships identified as part of answering research question #2 differ depending on whether or not instructional support for work with data was provided? a. How do the relationships between work with data, in general, and PECs differ on the basis of instructional support for work with data? b. How do the relationships between the specific aspects of work with data and PECs differ on the basis of instructional support for work with data? 4. Do the relationships between work with data and the PECs vary depending on students' pre-program interest in STEM? a. How do these relations differ for work with data on its own? b. How do these relations differ for work with data with support? 5. What are the common characteristics of potentially adaptive PECs beyond the presence of the aspects of work with data and other activities or the characteristics of learners?

Chapter 4

Method

This is a causal comparative study, in that explanations for differences in PECs are sought after their occurrence. 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.

4.1 Participants

Participants will consist of 203 youth. Students in these programs are from diverse racial and ethnic backgrounds. 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 Table 1.

Table 1 Demographic Characteristics of Learners

4.2 Context

The setting for this study will be 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 Table 2 with pseudonyms for the program names.

Table 2 STEM Enrichment Program Names and Their Descriptions

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.

4.3 Procedure

6045 9710 0447 9826

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 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.

4.4 Data Sources and Measures

Data sources will 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.

ESM measures of learners’ engagement and its conditions. Measures for engagement and its conditions will be 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 will be 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.

Table 3 ESM measures for profiles of engagement and its conditions (PECs)

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.

Table 4 Survey Measure Used in This Study

Codes for the activity from the video-recordings. Different aspects of work with data will be identified from video-recordings with the use of a coding frame with seven codes: five for each of the aspects of work with data and the remaining two codes are for other instructional activities, such as listening to a youth activity leader or completing a worksheet, in order to compare work with data to other activities which are potentially engaging but not oriented toward work with data, and one for other activities, such as traveling between program sites or the time in between activities. These codes are summarized in Table 5.

Table 5 Coding Frame for Work With Data

To determine the potential viability of this coding frame, observational notes from trained observers were analyzed. There were at least three observations for each of the nine programs. While these observation notes were collected only on a small number of days, video recordings of the programs (analyzed in the present study) were much more comprehensive. 31 observation notes were collected in total. A coding framework for work with data with three levels was used: 0 (no evidence of work with data), 1 (some evidence of work with data), and 3 (evidence of work with data). This analysis demonstrated that 36.6 % of notes revealed no evidence of work with data, 40 % of notes revealed some / potential evidence of work with data, and 23.3% revealed evidence of work with data.

In addition to the codes for aspects of work with data, all of the video are also coded as occurring in the classroom or in a field setting. These codes were created by research team members on the basis of documentation from the intermediary program providers, who alternated between classroom and field experiences on the basis of a set schedule. Furthermore, the videos are also coded regarding the instructional leader support for STEM-related practices created through the use of the Program Quality Assessment (Akiva, 2005). Accordingly, codes for instructional leader support for STEM practice to correspond to the codes for work with data will be created. These codes will equal to 1 only when both the aspect of work with data (in Table 5) is present as is the PQA code(s) associated with that aspect of work with data; accordingly, these codes will represent students' engagement in aspects of work with data that are also observed to be supported by youth instructional leaders. These codes are presented in Table 6.

Table 6 Coding Frame for Instructional Support for Work With Data

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

4.5 Data Analysis

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

Preliminary analyses. Codes for the aspects of work with data will be created from coding videos of the activity occurring immediately before learners were signaled to respond to a survey as part of the ESM. Before one rater independently codes the video associated with all of the signals, inter-rater reliability between the primary and a secondary rater will be established. The coding frame in Table 5 will be used to code a random sample of the videos associated with 30 of the ESM responses. The coding frame will be used to code for the presence of one and only one of the codes for the aspects of work with data. The agreement between the original and second rater will be calculated using Fleiss' kappa, with a value above .70 indicating satisfactory agreement. If the disagreement is not satisfactory, then cases in which the raters disagreed will be discussed and resolved, and a different sample of videos associated with ESM responses will be coded again. Following the satisfactory agreement, all of the videos associated with ESM signals will be coded independently: In order to provide to the coder the context to the video segments to be coded, all of the video segments will be viewed (but only those associated with ESM signals will be coded).

First-order Pearson correlations, frequency, range, mean, skew, kurtosis, and standard deviations will be 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 number of responses by student, program, and moment will be examined.

Primary analyses for RQ #1. To answer this question, PECs will be 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 will be 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. Particularly, 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.

Profiles will be 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 will be used as the dependent variable for subsequent analyses. An interface to the MCLUST software will be developed and used to carry out the LPA. The number of profiles will be 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. Scholars have pointed out the importance of cross-validation for mixture modeling (Steinley & Brusco, 2011); accordingly, double-split half cross-validation (Breckenridge, 2000) will also be carried out. Because of sampling error possible through the resampling needed for this approach, the cross-validation will be repeated at least 30 times for each candidate profile solution. 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.

Primary analyses for RQ #2. To answer this question, on how well the aspects of work with data predict the PECs, first, indicators for activities coded for any of the five aspects of work with data and either of the other two activities will be used to predict each PEC. This will help us to understand how work with data, in general, is different from other activities in terms of predicting each PEC. Next, how each of the five aspects of work with data, as well as the other activities, predict each PEC will be explored. This will help us understand how learners engage in specific aspects of work with data.

Due to similar mixed-effects models used to analyze data to answer RQ #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 will be used to provide answers to the specific research questions.

All of the models will 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 will be as many models as profiles identified in the preliminary analysis; so, the profile will be different between models. 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) will be specified. Then, the predictors will be 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 (obtained through the LPA carried out during the preliminary analyses) is predicted by the direct effects of indicators for the aspects of work with data ([replace]01 – [replace]05 below) measured at the momentary level, their individual interest in STEM ([replace]06), measured at the student level, and the random learner, moment, and program effects ([replace]learner, [replace]moment, and [replace]program). The general specification for the models for learner i during moment j in program k is written as:

Findings associated with this research question will help us understand how learners engage during different aspects of work with data and how engagement during the aspects of data differ from engagement during non-instructional activities. Another benefit of these models is the variance components, which can be interpreted in terms of the intraclass correlations. Because momentary and learner random effects are crossed and both nested with the program random effects, estimates for each of these random effects can provide information on the sources of unexplained variability in the PECs, thus helping us to understand the amount of variation that variables at each of the levels of the random effects (learner, moment, and program) can be explained.

Primary analyses for RQ #3. To answer this question, on how well the aspects of work with data with instructional support predict the PECs, first, indicators for activities coded for any of the five aspects of work with data will be interacted with a dummy code indicating instructional support in general, created on the basis of any of the variables for instructional support for work with data being equal to 1. This dummy coded variable will then be interacted with any of the aspects of work with data with relations to the PECs. Second, each of aspects of work with data with relations to the PECs will be interacted with a dummy code for the specific aspect of instructional support (in Table 6). This will help us to understand how work with data, in general and in terms of specific forms of instructional support, differs from other activities and how support from the instructor can contribute to more engaging work with data.

Primary analyses for RQ #4. To answer this question, on how the relationships between work with data and the PECs depends on students' pre-program interest in STEM, first, differences in the relationships between work with data in general and the PECs on the basis of students' individual interest in STEM will be explored, using an interaction between practices and individual interest in STEM. These analyses will be carried out separately for relations between work with data (on its own, corresponding to the analyses carried out for RQ #3) and work with data with instructional support (for RQ #4). Next, for any specific aspect of work with data that significantly predicts each PEC, the same will be carried out, so that the interaction between individual interest in STEM and the specific aspect of work with data will be used to predict each PEC. These interactions between individual interest in STEM and the dummy codes for aspects of work with data will be added to the model specification for RQ #2. Answers to this question will help us learn how the relationships between the PECs and the aspects of work with data vary on the basis of a trait-like characteristic of the learner may have important impacts. Given the exploratory nature of discovering which PECs emerge and how other factors relate to them, specific hypotheses are not made at this time.

Primary analyses for RQ #5. To answer this question, on the common characteristics of potentially adaptive PECs, a sequential exploratory data analysis strategy is 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 will be interrogated further for this research question.

The use of mixed effects models as part of the earlier research questions provides an especially useful strategy for selecting cases because the random moment effects represent moments that are associated with especially higher probabilities of responses associated with the different PECs. PECs will be identified and then coded qualitatively as part of an Extreme Case Approach. Selection of cases in this way also addresses a key challenge of the Extreme Case Approach, namely, how to present the variability among cases that may be selected because they are so different from the others—and from one another. The videos to select will be identified on the basis of moment-specific predictions accounting for all of the variables used to investigate the relations examined as part of question 2. If the moment-specific prediction for a potentially adaptive profile is especially positive and large, this suggests that there are characteristics of this moment that help to explain how students engaged in the aspects of work with data in highly engaging ways. Similarly, if the moment-specific prediction for a potentially maladaptive profile is especially negative and large, this suggests that there are characteristics of this moment that help to explain how this activity was not highly engaging. This analysis can help us to develop an account of what may distinguish these extreme cases from the majority with respect to the factors that influence engagement in work with data, as well as what may be particular to each specific case (Jahnukainen, 2010). 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.

In the first code-generating inductive step (Hatch, 2002), videos of the moments will be open-coded, in which notes and possible themes are recorded. Examples of potential codes include the factors influencing engagement in work with data presented in Figure 1: phenomena-based investigations, reference to or the presence of repeated cycles of engaging in work with data over time, and collaboration among learners. After open coding, notes and possible themes and the data will be read, and possible patterns in them will be recorded. These patterns will be collapsed into an initial coding frame, consisting of the codes, their description, and an example.

This coding frame is used in the second confirmatory step, which will involve a second rater, similar to the coding for the work with data carried out as part of the preliminary analysis. In the second step, the coding frame will be used to code for the presence of the codes in 20 of the video segments, randomly selected from among those identified as associated with random effects above the 80th percentile for the final models. Like in the preliminary analysis, the agreement between the original and second rater will be calculated using Fleiss' kappa, with a value above 0.70 indicating satisfactory agreement. If the agreement is not satisfactory, then cases in which the raters disagreed will be discussed and resolved, and a different sample of segments (if there is a sufficient number of samples; because only segments coded for one of the aspects of work with data will be sampled from) will be coded again. Knowing more about what other characteristics of the activity could impact the relationship between aspects of work with data and learners' engagement can help us to discover particular teaching strategies, instructional practices, and combinations of the aspects of work with data associated with engaging activities.

4.6 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).

4.7 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 5

Results

In this section, results in terms of the research questions are presented.

First, for RQ #1:

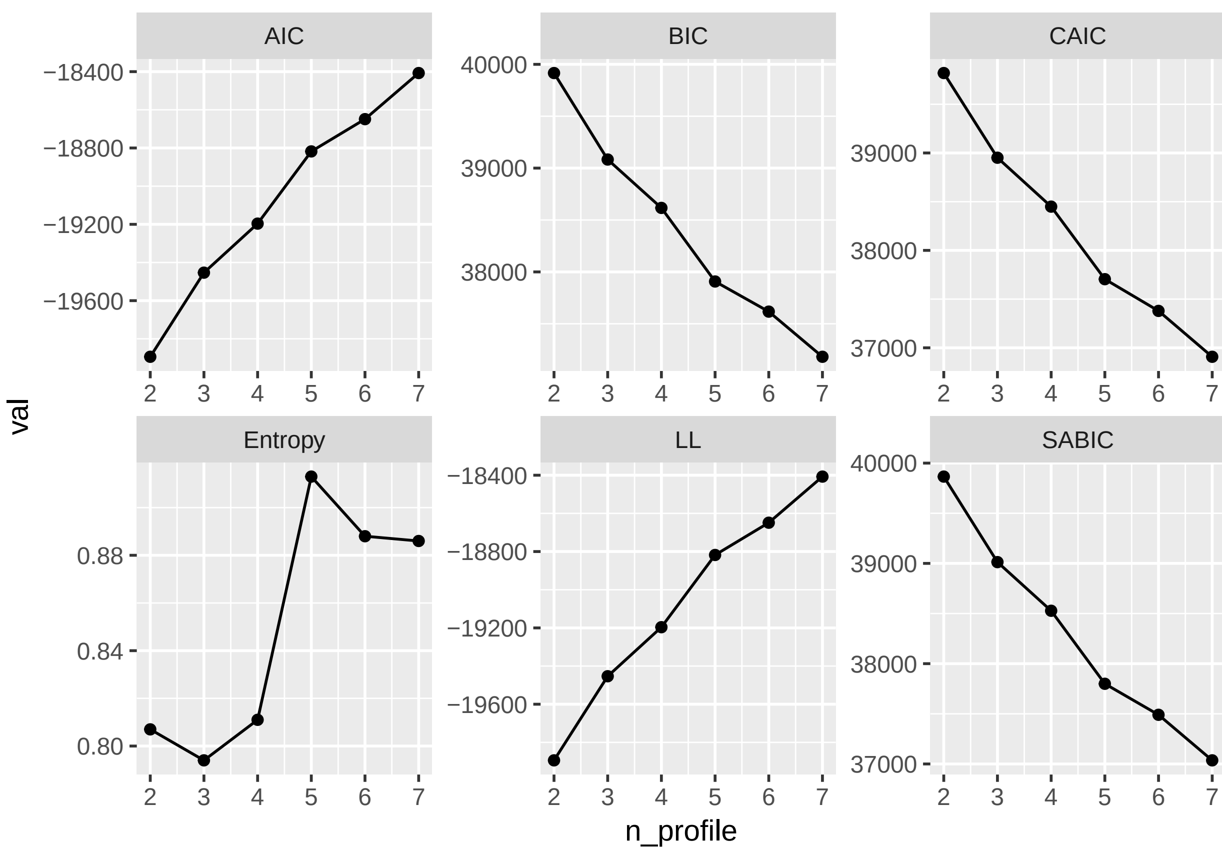
5.1 1. Solutions for all models

```
##   n_profiles                  model_1                  model_2
## 1          2                39916.157                38423.266
## 2          3                39082.592                38049.877
## 3          4                38616.439                37623.057
## 4          5                37907.604                37301.328
## 5          6                37617.262 Warning: LL not replicated
## 6          7                37182.108                 34517.58
## 7          8 Warning: LL not replicated Warning: LL not replicated
## 8          9 Warning: LL not replicated Warning: LL not replicated
## 9         10 Warning: LL not replicated Warning: LL not replicated
##                     model_3                  model_4
## 1 Error: Convergence issue Error: Convergence issue
## 2 Error: Convergence issue Error: Convergence issue
## 3 Error: Convergence issue Error: Convergence issue
## 4 Error: Convergence issue Error: Convergence issue
## 5 Error: Convergence issue Error: Convergence issue
## 6 Error: Convergence issue Error: Convergence issue
## 7 Error: Convergence issue Error: Convergence issue
## 8 Error: Convergence issue Error: Convergence issue
## 9 Error: Convergence issue Error: Convergence issue
##                     model_5                  model_6
## 1 Error: Convergence issue Error: Convergence issue
## 2 Error: Convergence issue Error: Convergence issue
## 3 Error: Convergence issue Error: Convergence issue
## 4 Error: Convergence issue Error: Convergence issue
## 5 Error: Convergence issue Error: Convergence issue
## 6 Error: Convergence issue Error: Convergence issue
## 7 Error: Convergence issue Error: Convergence issue
## 8 Error: Convergence issue Error: Convergence issue
## 9 Error: Convergence issue Error: Convergence issue
```

5.2 2. Just for model 1

```
##   n_profiles                   model_1
## 1          2                 39916.157
## 2          3                 39082.592
## 3          4                 38616.439
## 4          5                 37907.604
## 5          6                 37617.262
## 6          7                 37182.108
## 7          8 Warning: LL not replicated
## 8          9 Warning: LL not replicated
## 9         10 Warning: LL not replicated
```

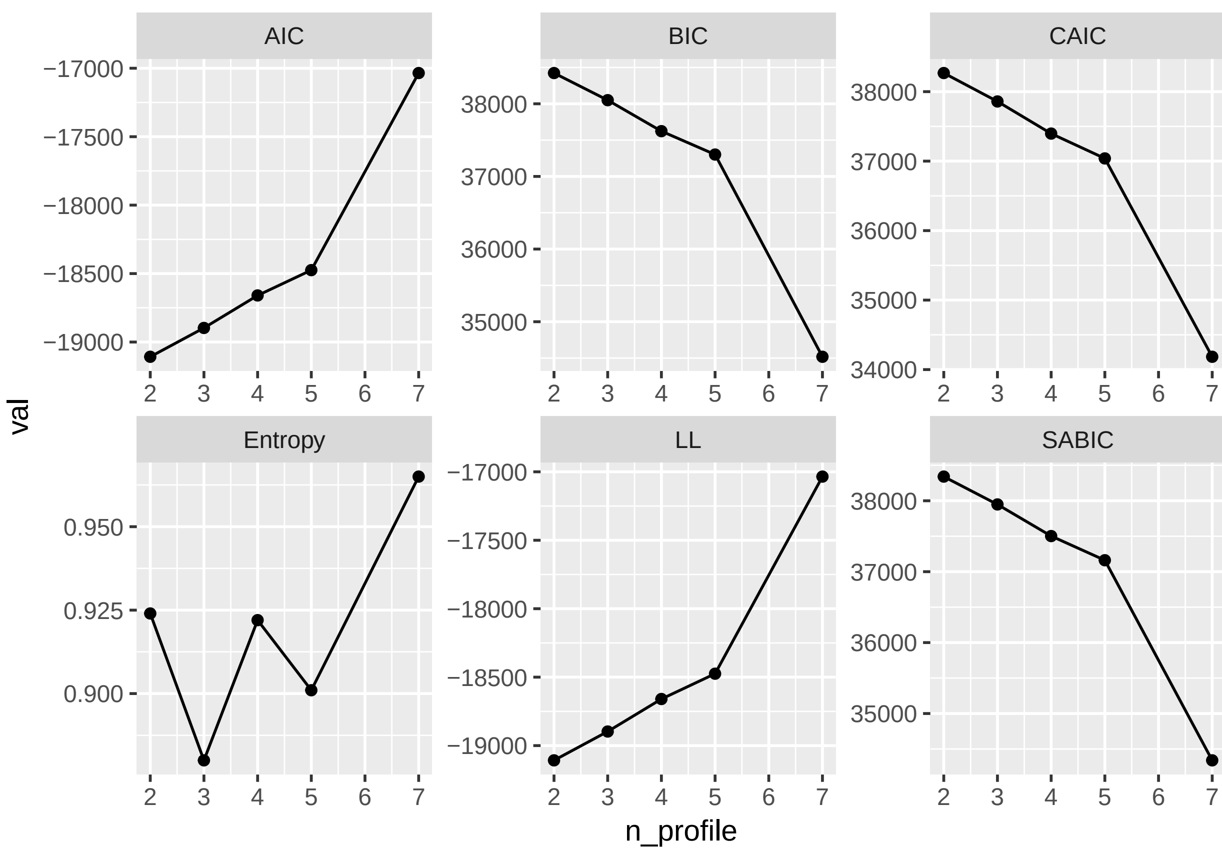
```
##   n_profile model        LL       AIC      BIC    SABIC     CAIC Entropy
## 1         2     1 -19894.14 -19894.14 39916.16 39865.32 39820.47   0.807
## 2         3     1 -19453.38 -19453.38 39082.59 39012.69 38951.11   0.794
## 3         4     1 -19196.33 -19196.33 38616.44 38527.47 38449.21   0.811
## 4         5     1 -18817.93 -18817.93 37907.60 37799.57 37704.68   0.913
## 5         6     1 -18648.78 -18648.78 37617.26 37490.17 37378.70   0.888
## 6         7     1 -18407.23 -18407.23 37182.11 37035.95 36907.95   0.886
##   VLMR_val VLMR_p  LMR_val  LMR_p BLRT_val BLRT_p
## 1 3468.199 0.0000 3397.353 0.0000 3468.199      0
## 2  881.519 0.0126  863.512 0.0136  881.519      0
## 3  514.107 0.0000  503.605 0.0000  514.107      0
## 4  756.788 0.0000  741.329 0.0000  756.788      0
## 5  338.296 0.0000  331.386 0.0000  338.296      0
## 6  523.141 0.0112  512.455 0.0121  523.141      0
```



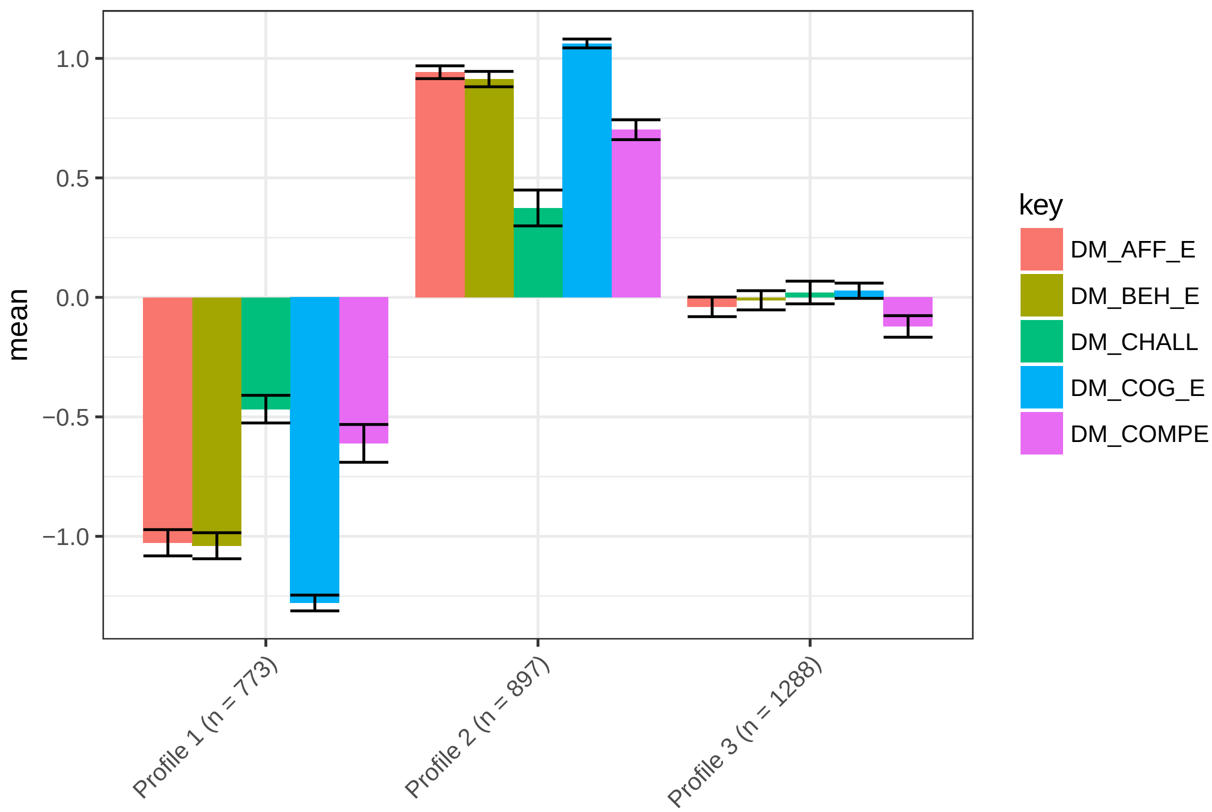
5.3 2. Just for model 2

```
##   n_profiles model_2                        V3
## 1          2      NA                 38423.266
## 2          3      NA                 38049.877
## 3          4      NA                 37623.057
## 4          5      NA                 37301.328
## 5          6      NA Warning: LL not replicated
## 6          7      NA                  34517.58
## 7          8      NA Warning: LL not replicated
## 8          9      NA Warning: LL not replicated
## 9         10      NA Warning: LL not replicated
```

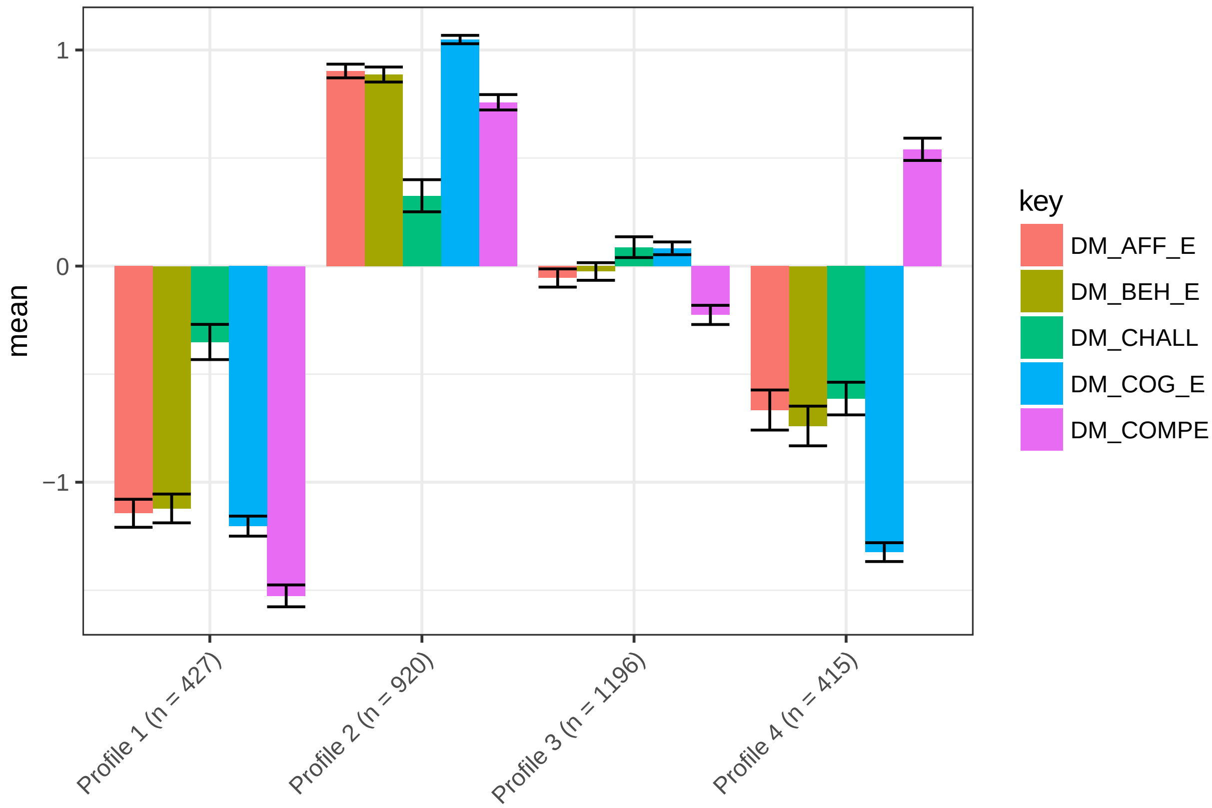
```
##   n_profile model        LL       AIC      BIC    SABIC     CAIC Entropy
## 1         2     2 -19107.73 -19107.73 38423.27 38340.65 38267.95   0.924
## 2         3     2 -18897.06 -18897.06 38049.88 37948.20 37858.85   0.880
## 3         4     2 -18659.68 -18659.68 37623.06 37502.32 37396.37   0.922
## 4         5     2 -18474.83 -18474.83 37301.33 37161.52 37039.03   0.901
## 5         7     2 -17035.01 -17035.01 34517.58 34339.65 34184.21   0.965
##   VLMR_val VLMR_p   LMR_val  LMR_p BLRT_val BLRT_p
## 1  850.304      0   832.934 0.0000  850.304      0
## 2  421.343      0   412.736 0.0000  421.343      0
## 3  474.773      0   465.075 0.0000  474.773      0
## 4  304.938      0   298.709 0.0000  304.938      0
## 5       NA     NA -1374.094 0.8708       NA     NA
```



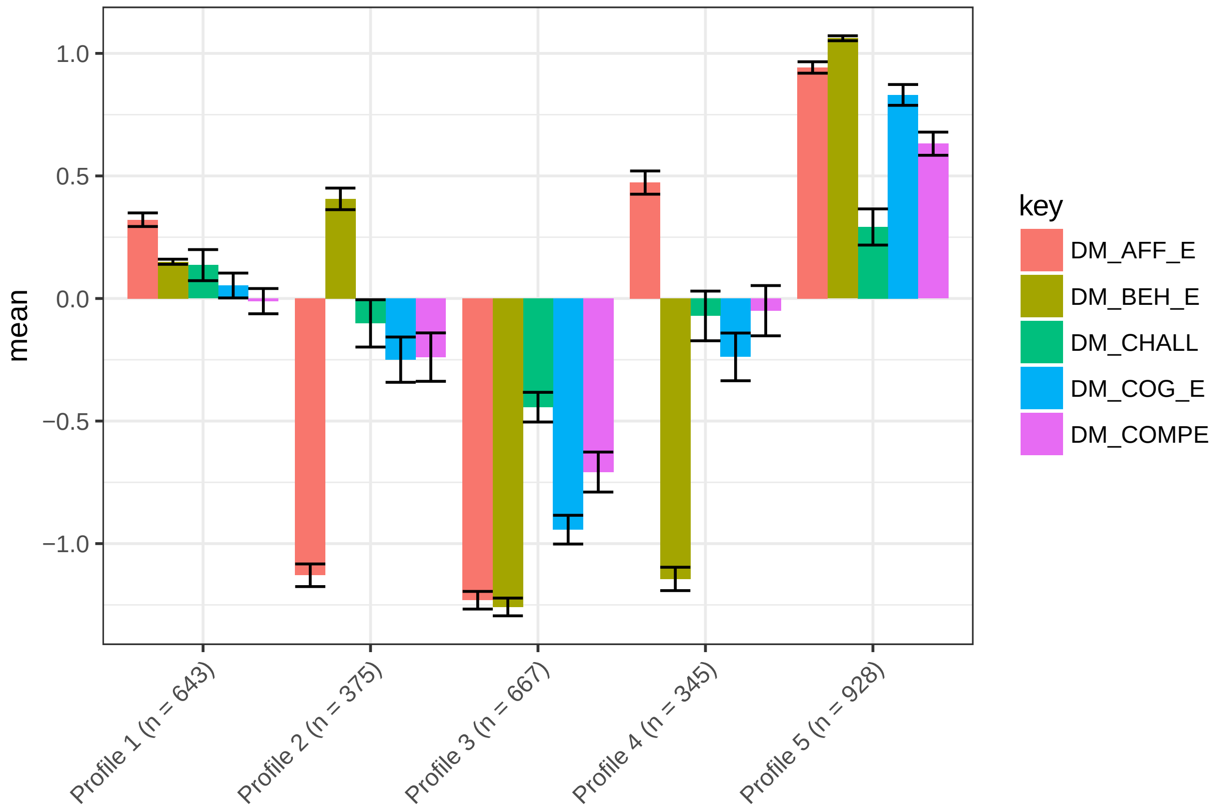
5.4 4. Some specific solutions for model 1



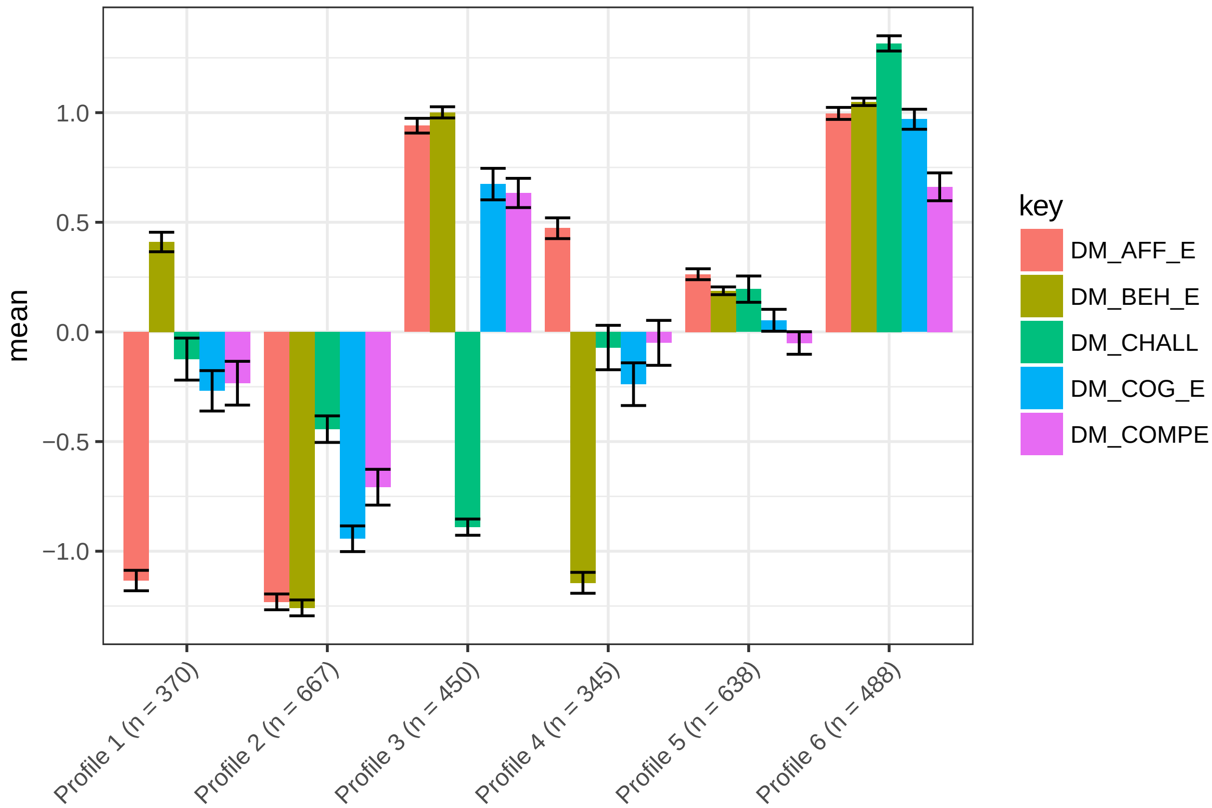

```
## # A tibble: 119 x 3
##    LL              seed m_iterations
##  * <fct>          <dbl> <chr>
##  1 -19453.381 231281 542
##  2 -19453.381 897782 545
##  3 -19453.381 155622 507
##  4 -19453.381 879211 453
##  5 -19453.381 192071 142
##  6 -19453.381 507154 387
##  7 -19453.381 674171 195
##  8 -19453.381 316165 299
##  9 -19453.381 374219 353
## 10 -19453.381 783102 433
## # ... with 109 more rows
```



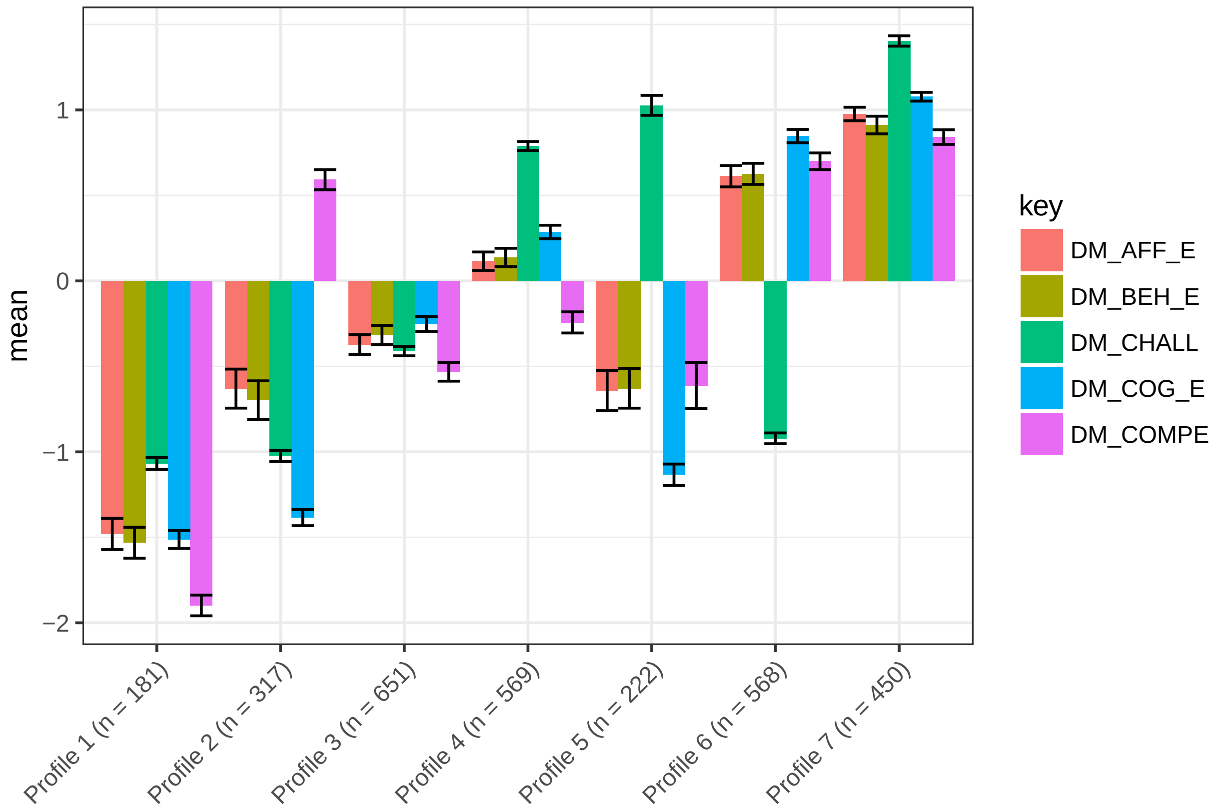

```
## # A tibble: 80 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -19196.328 415931 10
##  2 -19196.328 260953 589
##  3 -19196.328 576220 115
##  4 -19196.328 329127 185
##  5 -19196.328 391179 78
##  6 -19196.328 352277 42
##  7 -19196.328 443442 380
##  8 -19196.328 518828 432
##  9 -19196.328  36714 201
## 10 -19196.328 456213 160
## # ... with 70 more rows
```



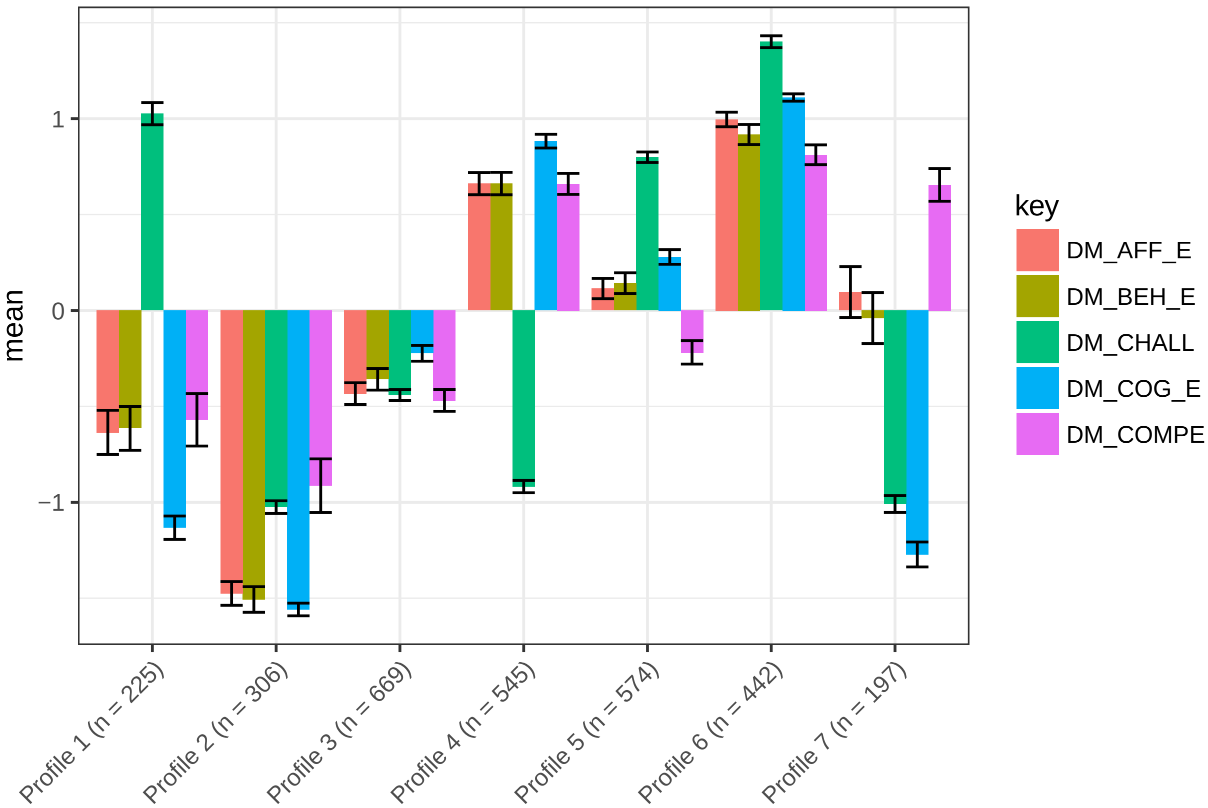

```
## # A tibble: 82 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -18817.934 152496 123
##  2 -18817.934 602797 336
##  3 -18817.934 432148 30
##  4 -18817.934 399848 220
##  5 -18837.053 387701 275
##  6 -18858.428 850545 357
##  7 -18858.428 298275 418
##  8 -18858.428 626891 32
##  9 -18944.968 823392 479
## 10 -18944.968 147440 514
## # ... with 72 more rows
```




```
## # A tibble: 64 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -18648.785   1548 384
##  2 -18648.785 282464 283
##  3 -18668.802 529496 343
##  4 -18695.729  49221 254
##  5 -18695.729 153394 429
##  6 -18695.729 741888 138
##  7 -18695.729  85114 385
##  8 -18695.729 173191 422
##  9 -18695.729 436460 89
## 10 -18695.729 153942 31
## # ... with 54 more rows
```

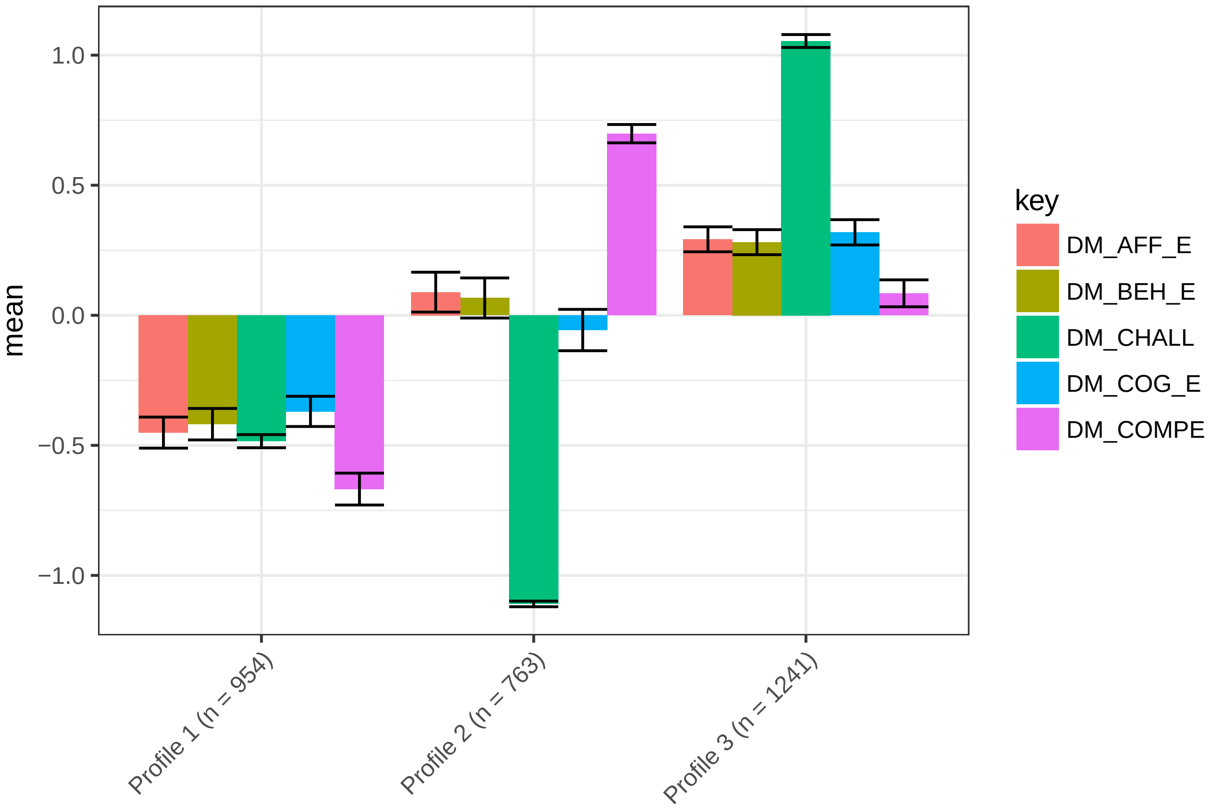



```
## # A tibble: 52 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -18407.232 475420 71
##  2 -18407.232 871438 561
##  3 -18469.834 597614 284
##  4 -18469.834 830570 369
##  5 -18469.834 283492 435
##  6 -18469.834 260953 589
##  7 -18518.118 153394 429
##  8 -18634.678 950604 172
##  9 -18660.958 922596 456
## 10 -18662.856 160326 546
## # ... with 42 more rows
```

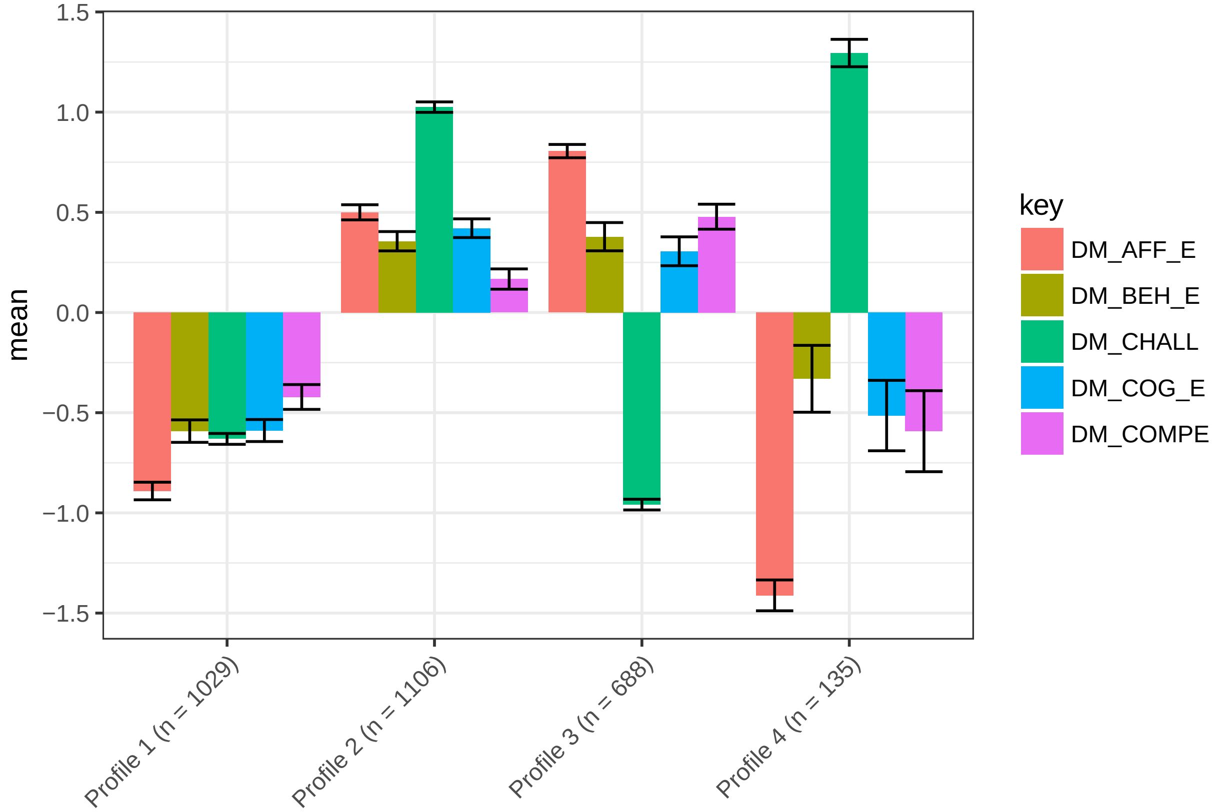


mean
1
0
−1
Profile 1 (n = 225)
Profile 2 (n = 306)
Profile 3 (n = 669)
Profile 4 (n = 545)
Profile 5 (n = 574)
Profile 6 (n = 442)
Profile 7 (n = 197)
key
DM_AFF_E
DM_BEH_E
DM_CHALL
DM_COG_E
DM_COMPE

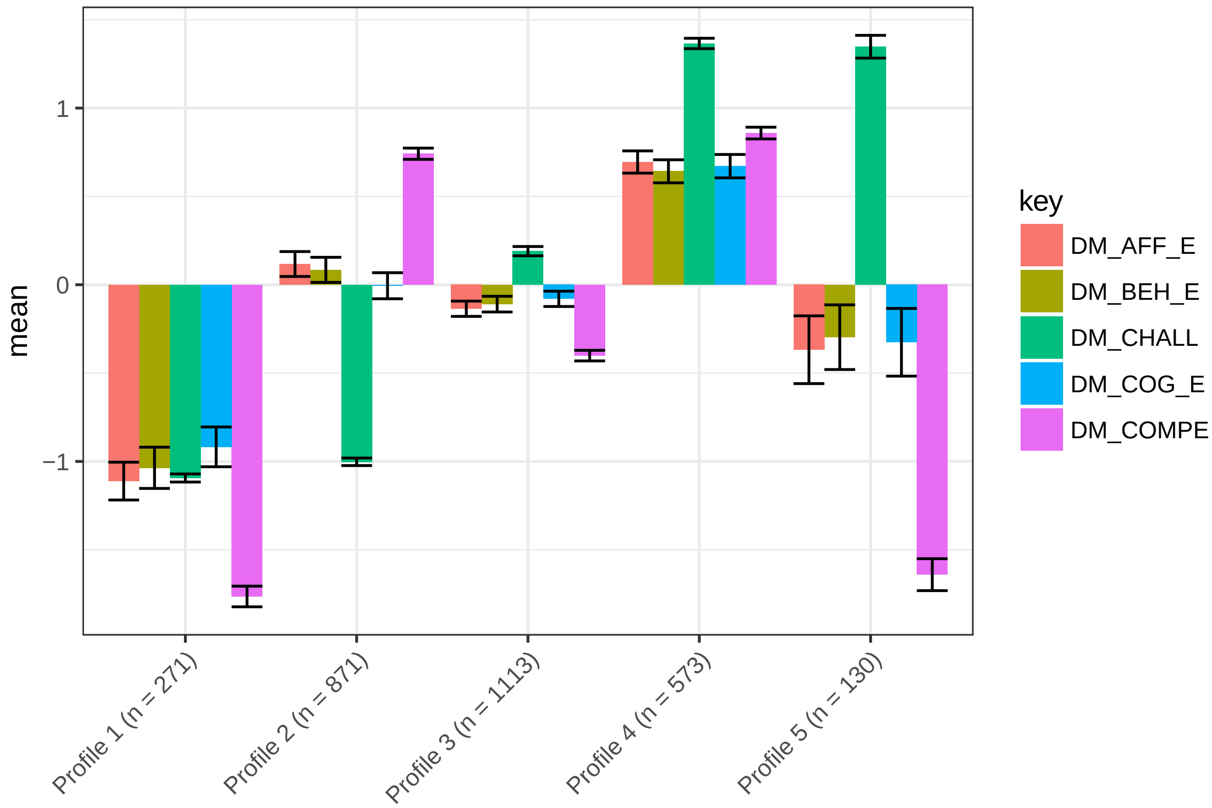
5.5 5. Some specific solutions for model 2




```
## # A tibble: 120 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -18897.062 154575 539
##  2 -18897.062 606576 151
##  3 -18897.062 746978 410
##  4 -18897.062 107446 12
##  5 -18897.062  30098 209
##  6 -18897.062 871851 257
##  7 -18897.062 491970 563
##  8 -18897.062  76451 211
##  9 -18897.062 152496 123
## 10 -18897.062 458181 189
## # ... with 110 more rows
```



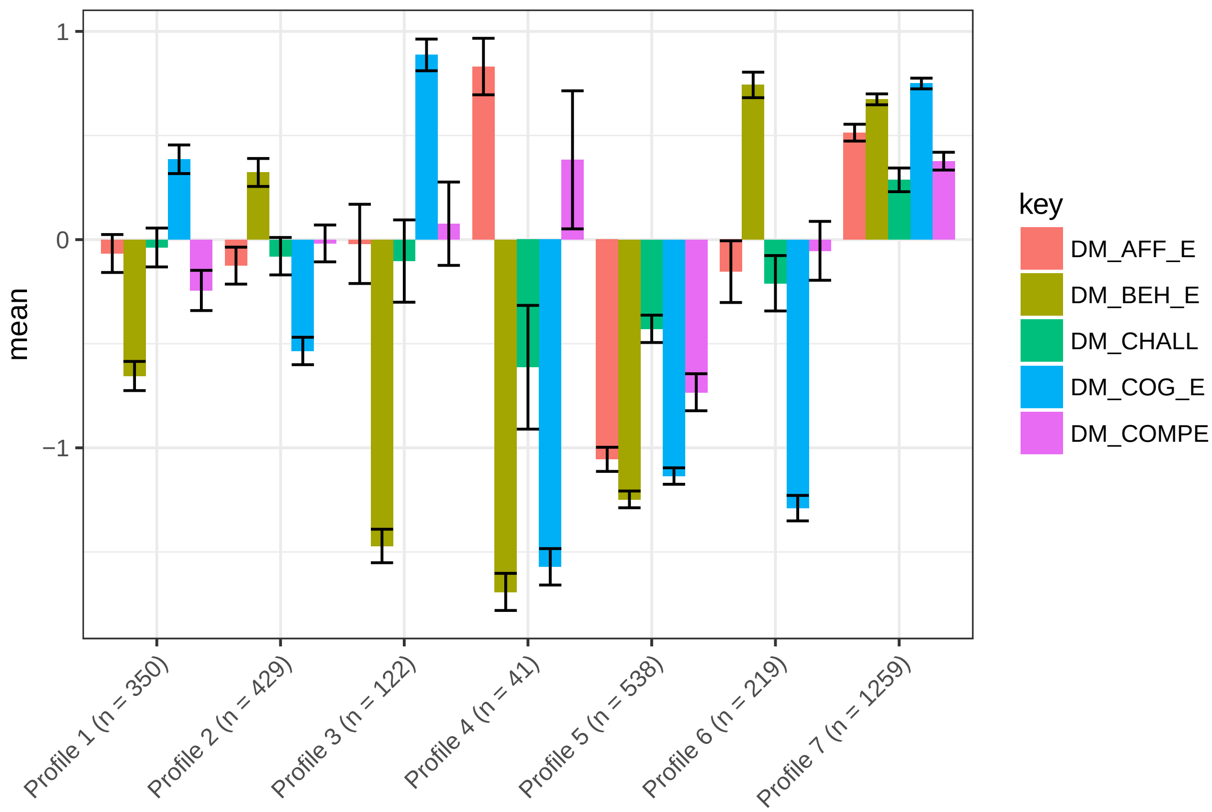

```
## # A tibble: 119 x 3
##    LL           seed m_iterations
##  * <chr>       <dbl> <chr>
##  1 -18659.676 286735 175
##  2 -18659.676 349562 359
##  3 -18659.676 568859 49
##  4 -18686.131 562716 300
##  5 -18690.761 475420 71
##  6 -18690.761 147440 514
##  7 -18690.761 279850 555
##  8 -18690.761 667250 318
##  9 -18690.761 153394 429
## 10 -18709.289 327475 518
## # ... with 109 more rows
```




```
## # A tibble: 114 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -18474.834 154575 539
##  2 -18474.834 436460 89
##  3 -18474.834 746978 410
##  4 -18474.834  85114 385
##  5 -18479.167 217130 443
##  6 -18479.167 539389 544
##  7 -18481.815 407108 366
##  8 -18481.815 165853 105
##  9 -18481.815  73576 213
## 10 -18481.815 471398 74
## # ... with 104 more rows
```

```
## # A tibble: 104 x 3
##    LL            seed m_iterations
##  * <chr>        <dbl> <chr>
##  1 -17098.434 344422 296
##  2 -17216.914 226322 478
##  3 -17714.856 853195 431
##  4 -18285.363 153053 378
##  5 -18304.150 211281 292
##  6 -18304.150 529496 343
##  7 -18320.492 350608 334
##  8 -18323.206 691234 250
##  9 -18337.703 425929 508
```

```
## 10 -18337.703 153394 429
## # ... with 94 more rows
```




```
## # A tibble: 97 x 3
##    LL            seed m_iterations
##    * <chr>       <dbl> <chr>
##  1 -17035.006  85734 411
##  2 -17035.006 344422 296
##  3 -18213.406 939021 8
##  4 -18214.792 458181 189
##  5 -18217.063 715255 523
##  6 -18227.574 126371 526
##  7 -18227.574 391949 295
##  8 -18234.603  30098 209
##  9 -18234.603 150531 154
## 10 -18234.603 790452 303
## # ... with 87 more rows
```

Chapter 6

Discussion

Chapter 7

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