# 

# 

# 

# 

# 

Using Momentary Engagement Profiles to Understand Learners’ Data Modeling in Out-of-School Time Enrichment Programs

A Dissertation Proposal

Joshua M. Rosenberg

Michigan State University

Table of Contents

Introduction 4

Literature Review 6

Defining Data Analysis and the Role of Data Modeling 7

What We Know (And Do Not Know) About Data Modeling 11

Engagement in STEM Domains 13

The Present Study 19

Conceptual Framework 19

Research Questions 22

Method 23

Participants 24

Context 25

Procedure 28

Data Sources and Measures 29

Data Analysis 31

References 39

# Abstract

Data are essential to making sense of the world. Many occupations ask us to analyze data, and in many areas of study, data analysis can provide the opportunity to not only learn about STEM content, but also how to engage in and do what those engaged in STEM disciplines do. Despite how common data analysis is in the practice of STEM and other professions, and the role of data analysis and modeling in both science and engineering and mathematics curricular standards, opportunities for learners to engage with data remain limited. A key challenge and limitation to what we know about learners’ data analysis in STEM settings has to do with their engagement, how they are thinking, feeling, and behaving while doing analyzing data. This proposed study uses contemporary engagement theory to understand whether engaging in data modeling differs from engaging in other activities. Additionally, how challenging learners perceive an activity to be, and how good at it they perceive they are, are used to explain potential differences in engagement between data modeling and other activities. An approach combining Experience Sampling Methodology, in which students are asked to respond to brief questions about their experience when they were signaled, and a person-oriented approach, considering engagement in terms of different patterns among the individual components of engagement that are experienced together as a combined effect, characterized as Momentary Engagement Profiles. Knowing more about whether and how learners engage in data modeling and how learners’ perceptions of challenge and competence can help us to make informed recommendations to teachers for designing and enacting opportunities for learners to use data to make sense of their world.

# Introduction

Data analysis includes processes of not only creating, or collecting, data, and modeling data, but also asking empirical questions and interpreting findings. Thinking with data is a shared goal for many STEM educators and stakeholders. This is because thinking with data is not just about using data—it is not about crunching numbers, or interpreting a figure created by someone else—but rather using data to make sense of something (Lovett & Shah, 2007). Cutting across STEM domains, its elements are found 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). Furthermore, there are suggestions that it “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).

Despite these known benefits, opportunities for students to analyze data with understanding in K-12 STEM settings remain limited. Much of the research in science settings focuses on evidence use (McNeill & Berland, 2017). Creating and constructing models of primary data takes ample time (Dickes, Sengupta, Farris, & Basu, 2016), and doing so in mathematics settings is uncommon (Lehrer & Schauble, 2015). Providing opportunities for students to 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).

There is little research examining how learners do data modeling in terms of their engagement. What learners are thinking and feeling and how they are behaving while asking questions and identifying problems, constructing measures, modeling data, and interpreting findings has been the focus of less research, but understanding these may be important outcomes for understanding whether engaging in data modeling differs from engaging in other activities. Additionally, little research has explained differences in how learners engage in data modeling in terms of key moderators of engagement, challenge and competence, which can be considered as motivational reasons explanations for why there are differences.In other STEM settings, engagement is a predictor of important learning-related outcomes (Sinatra, Heddy, & Lombardi, 2015), and so engagement in data modeling may be important predictors of outcomes from data modeling. Additionally, what learners are thinking, feeling, and doing when engaging in data modeling may also be important to learners’ preparation for future learning (Bransford & Schwartz, 1999), especially in data-rich areas of studies and occupations, such as data science. A potential direction for understanding data modeling, then, is to understand whether learners’ experiences of doing modeling relate to their engagement, and how learners perceptions of how challenge the activity is or how competent they are could explain differences in engagement in data modeling.

Contemporary engagement theory offers a potentially appealing framework with which to understand the experience of doing data analysis because it considers multiple dimensions of engagement (commonly cognitive, behavioral, and affective) and its dynamic nature (Fredricks, 2016). Some engagement scholars committed to understanding what impacts the dynamics of engagement have drawn upon flow theory (Csikszentmihalyi, 1990, 1997) to identify how learners’ perceived competence and challenge act as key influencers of engagement (Shernoff et al., 2016).

The purpose of this study, then, is to understand the experience of data modeling through the lenses of engagement using a person-oriented approach. Outside-of-school programs are selected as the setting because of their affordance for exploring data modeling in settings suited to it. Staff for these programs includes educators and scientists, engineers, and others with the technical experience helpful for supporting learners’ data modeling. Additionally, the programs were designed to involve learners in the types of real-world practices experienced by experts in STEM disciplines. These programs are also selected because 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. While these reasons are for outside-of-school programs, they are also germane to more formal learning environments, such as classrooms, in which teachers want to design opportunities to work with data to their learners, and who may themselves have technical expertise, but who have experienced limited training and support for engaging learners in data modeling in the past. Therefore, these programs can provide insight into whether engaging in data modeling is associated with more optimal forms of engagement in the conditions like those for classrooms in which data modeling is a novel and potentially promising approach to doing and learning about STEM.

# 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 data modeling as a subset of data analysis highlighting the importance of accounting for variability that may be especially useful as a pedagogical approach to doing data analysis in K-12 settings. This section also reviews what is currently not known about data modeling, and introduces engagement and influencers of engagement to establish the conceptual framework use in the present study.

## Defining Data Analysis and the Role of Data Modeling

Some scholars have focused on a few key pieces of data analysis to capture the process 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, termed by some scholars as *data modeling*, is commonly described with two goals, data creation and data analysis (English, 2012; Hancock et al., 1992; Lehrer & Romberg, 1996; Lesh, Middleton, Caylor, & Gupta, 2008; Nemirovski, Kaput, & Roschelle, 1998). This approach has primarily been taken up by mathematics educators, including statistics educators (Lee & Tran, 2015; Wild & Pfannkuch, 1999), reflected in statistics curriculum documents (Franklin et al., 2007). In science settings, where answering questions about phenomena serves as the focus of activities, it shares features of the process of engaging in scientific and engineering practices, but has been less common.

Scholars have conceived of data modeling in different ways, but some core components remain. 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 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 data modeling, the process of “using data to solve real problems and to answer authentic questions” (p. 337). Hancock focus in on two goals, data creation and analysis, arguing that the former (data creation) is “the neglected counterpart of data analysis” (p. 339). Scholars have subsequently expanded Hancock et al’s definition of data modeling 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, for use of this conceptualization of data modeling to understand how and why plants grow). The last of these is crucial across all of the visions of data modeling reviewed here, distinguishing 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.

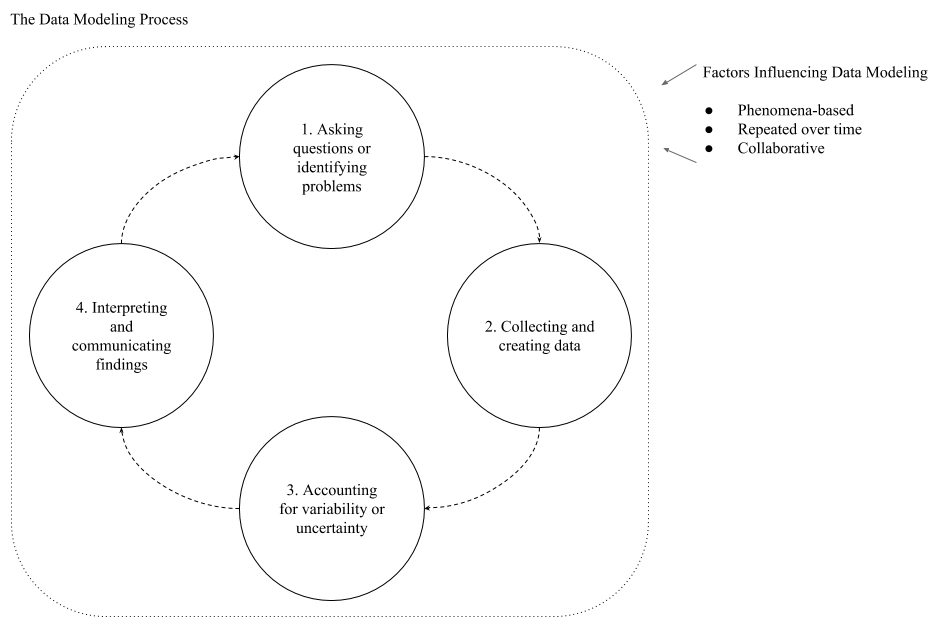
One way to develop an account is to focus on what is common across these accounts of the process of data modeling. All involve asking questions. The process of measuring is described in each, though with differences in definitions (Franklin et al. describe the process as collecting data, while Lehrer and Schauble describe separate processes of constructing measures and measuring, for example). Analyzing data, or more formally in most settings, accounting for variability or uncertainty, is common to each. Finally, in none of the processes does data modeling end with the analysis or model: Finding how the analyses or model provides an answer to the question posed, or interpreting the findings, is key.

Data modeling, then, includes four 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, collecting and creating data, accounting for variability or uncertainty, and interpreting and communicating findings. In addition, scholars have pointed out some key features of how data modeling is carried out that impact its effectiveness as a pedagogical approach: that it is based on making sense of real-world phenomena, that it involves iterative cycles, in which what counts as data is transformed over time, and that it involves collaboration and dialogue, in which ideas and intermediate findings are critiqued and subject to critique, and revised over time (McNeill & Berland, 2016).

The four processes, as depicted in Figure 1, are a cycle because not only does each part follow that before it, but also because interpreting findings commonly leads to revised or new questions, which leads to the need for the subsequent data modeling processes. The first process, asking questions, is about generating questions that can be answered with empirical evidence. The next, creating and collecting data, is about identifying potential sources of data and ways to measure them, and carrying out the process of transforming observations into data. Data are messy, and analyzing, or modeling, data follows from its creation or collection. The last step is to interpret and communicate findings in terms of the phenomena the question is about.

Figure 1.

*The process of data modeling and the factors influencing it.*



Scholars argue that data modeling 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. Also important, becoming proficient at data modeling can provide learners’ in-demand and potentially powerful capacity within society (Finzer, 2013). Because of recent reform efforts emphases on 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), yet the relative rarity and challenge of work with data in many classroom settings (McNeill & Berland, 2016), learning environments suited to data modeling, but not explicitly designed to support it, may be valuable to study.

The data modeling process 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 takes many forms, from learning about what we already know to systematic efforts to measure large, small, or hard to study phenomena. Data analysis, like data modeling, 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, 2012). Many policy and curricular documents characterize data analysis as using data to explain or predict phenomena (i.e., NGSS Lead States, 2013; National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010; NGSS Lead States, 2013). Because of the range of capabilities included within data analysis is large, 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), and so data modeling, more specific and limited than data analysis in its broader sense, is the focus of the present study.

## What We Know (And Do Not Know) About Data Modeling

We know about data modeling—what learners are capable of and how to support it—from both laboratory- and design-based research studies. This research has been carried out by developmental and educational psychologists as well as by mathematics and science educators. Findings from these studies and what we know less about are discussed in this section.

First, scholars have carried out research about specific cognitive capabilities related to data modeling. 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 data modeling has to do with how learners account for variability (Lehrer, Kim, & Schauble, 2011; Nemirovski, Kaput, & Roschelle, 1998; Petrosino, Lehrer, & Schauble, 2003; Lesh, Middleton, Caylor, & Gupta, 2008; Lee, Angotti, & Tarr, 2010), arguably the key goal of data modeling (Konold & Pollatsek, 2002). From this research, we know that learners can develop the capacity to reason about variability and covariability

Second, while young learners have the ability to develop sophisticated reasoning about data, this kind of reasoning about data may be less common in many school settings. Many researchers, therefore, have sought to identify learning environments supportive of data modeling, such as after-school programs, or design learning environments*.* We know that different parts of data modeling pose different challenges. Asking empirical questions requires experience and ample time in order to ask a question that is both able to be answered with data and which is sustaining and worth investigating (Bielik, 2017; Hasson & Yarden, 2012). In terms of modeling, not only teaching students about models, such as that of the mean, but also asking them to create them, are both valuable but also time-consuming (Lehrer & Schauble, 2004). Finally, interpreting findings, especially in light of variability through models, and communicating answers to questions from the process of data modeling, 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).

Third, specific outcomes have been explored through modeling data. Research on designing environments conducive to data modeling has included curricula, specific instructional strategies supported through collaborations between researchers and teachers, and technological tools. 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).

While we know a great deal about what learners can do during different aspects of data modeling as well as outcomes achieved through data modeling, what learners are thinking and believing at these times has been studied less. 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, 2015). How challenging do students perceive these tasks to be? How to they perceive their competence with respect to this task? 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 data modeling in better supported and sustaining ways, such as what makes it hard to do data modeling. Is it that certain parts are inherently less engaging? That learners perceive data modeling to be hard?

## Engagement in STEM Domains

The nature of engagement in general, or across domains, and differences between engagement in general and in STEM settings is discussed, followed by 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 a useful construct for understanding involvement in activity. It often is conceptualized as a meta-construct, that is, one that consists of other constructs (Skinner et al., 2012; Skinner, Kindermann, & Furrer, 2009). The focus of engagement on involvement means that engagement is useful for explaining how people do activities; accordingly, it is less useful for explaining why they do, something motivation-related constructs offer greater explanatory power for. Explaining how learners do activities is especially important if we want to know about what aspects of data modeling are most engaging (and in what ways), and therefore can serve as exemplary for others advancing data modeling activities, as well as those calling for greater support for engagement.

Recent scholarship has summarized key characteristics of engagement and outcomes from engaging at school and in other learning environments (Fredricks, 2016b). Behavioral engagement is important because of the importance of exerting effort to learning. Cognitive engagement is important because learning regularly involves developing new knowledge, capabilities, and problem-solving strategies. Affective engagement is important because liking an activity is associated with stronger motivation and outcomes such as choosing a major and career. 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.

*Differences between engagement in general and engagement in STEM domains.* Engagement in STEM settings shares characteristics with engagement across disciplines, yet there are some distinct aspects of it (Greene, 2014). By defining engagement as a meta-construct, scholars characterize in in terms of behavioral, cognitive, and affective dimensions that are distinct yet interrelated (Fredricks, 2016). We know from past research that the behavioral, cognitive, 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, 2016), careful justification and thoughtful use of multidimensional engagement constructs and measures is warranted based on past research. 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 of cognitive engagement with implications for measures of engagement. Because of the importance of constructing knowledge to engagement in STEM practices, measures of cognitive engagement may emphasize students’ perception that they are learning something new, whereas past measures have focused on use of learning and meta-cognitive strategies and value, and sometimes pursuit of intellectual goals (Fredricks et al., 2004) Fredricks & McColskey, 2012). While sometimes defined in terms of extra-curricular involvement or following directions, behavioral engagement is commonly defined as emphasize working hard at and concentrating in learning-related activities (Fredricks et al., 2004). Finally, while affective engagement can be considered in terms of value-related beliefs (Fredricks et al., 2004), because value-related beliefs capture why learners engage, rather than how, affective engagement can be usefully defined as affective responses to activities (Pekrun & Linnenbrink-Garcia, 2012).

*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. 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 answer 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).

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. Shernoff et al. (2013) examined engagement through 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. This past research that used ESM 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.

In particular for engagement—about involvement in activities—past research has shown that ESM can help us to find out what influences it.Past research suggests that momentary, dynamic influencers can predict engagement. A key momentary influencer is how hard individuals perceive an activity is, or its perceived challenge. Another key influencer is how good at an activity individuals perceive themselves to be, or their perceived competence. Most important, being challenged by and good at an activity can be more engaging experienced together (Shernoff et al., 2016). For example, Shernoff et al. (2013) demonstrated that while challenge and skill with high levels of one but low levels on the other (i.e., anxiety, or 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 task, and their perceptions of how skillful they are, are important for explaining why learners engage.

*A person-centered approach to engagement.* One powerful and increasingly widely-used way to examine dynamic constructs in a holistic way, sometimes referred to as a person-oriented approach, is to consider the way in which measured variables group together in the experiences of learners This view, developed within developmental science, emphasizes these groups in light of the dynamic nature of development, and the importance of intra-individual, social, cultural, and contextual factors upon these dynamics (Bergman & Magnusson, 2002; Magnusson & Cairns, 1996; Thelen & Smith, 2003). It can be contrasted with variable-oriented analyses, although person-oriented studies are often useful in conjunction with such analyses. Such studies examining learning from person-oriented perspective are uncommon, yet examples considering intrinsic and extrinsic motivation (Corpus & Wormington, 2014; Hayenga & Corpus, 2010), epistemic considerations (Trevors, Kendeou, Braten, & Braasch, 2017), and profiles of achievement goals (see Wormington & Linnenbrink-Garcia, advance online publication for a review).

There are some recent studies taking a person-oriented approach to the study of engagement (i.e., Salmela-Aro, Muotka, Alho, Hakkarainen, & Lonka, 2016b; Van Rooij, Jansen, & van de Grift, 2017; Salmela-Aro, Moeller, Schneider, Spicer, & Lavonen, 2016a; Schmidt, Rosenberg, & Beymer, in press). 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.

The person-oriented approach has an important implication for how we consider engagement, especially when we consider it to be dynamic. When past studies have constructed profiles of engagement, as described in this section, it is common to predict these profiles using other measures, such as of momentary resources and demands (Salmela-Aro et al., 2016b). 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.

In a forthcoming study, Schmidt, Rosenberg, and Beymer (in press), further explored this relation between engagement and laboratory activities. In particular, laboratory-related activities, especially those that learners perceived as offering them greater choice in the goals of the activity, the framing, 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 the process of data modeling, in which learners have to make choices about how to carry out the analysis, may be important predictors of engagement. This study also 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 activity.

In summary, most studies of engagement have considered it in terms of the individual components of engagement, rather than in terms of profiles of engagement. Viewing engagement in terms of profiles has two primary benefits. First, teachers and other stakeholders may be able to notice and adapt their teaching in response to learners’ engagement profiles better than indicators of independent dimensions of engagement. Second, researchers may be able to use profiles to consider what engagement-related factors underlying cognitive, behavioral, and affective dimensions of engagement learners’ experience.

# The Present Study

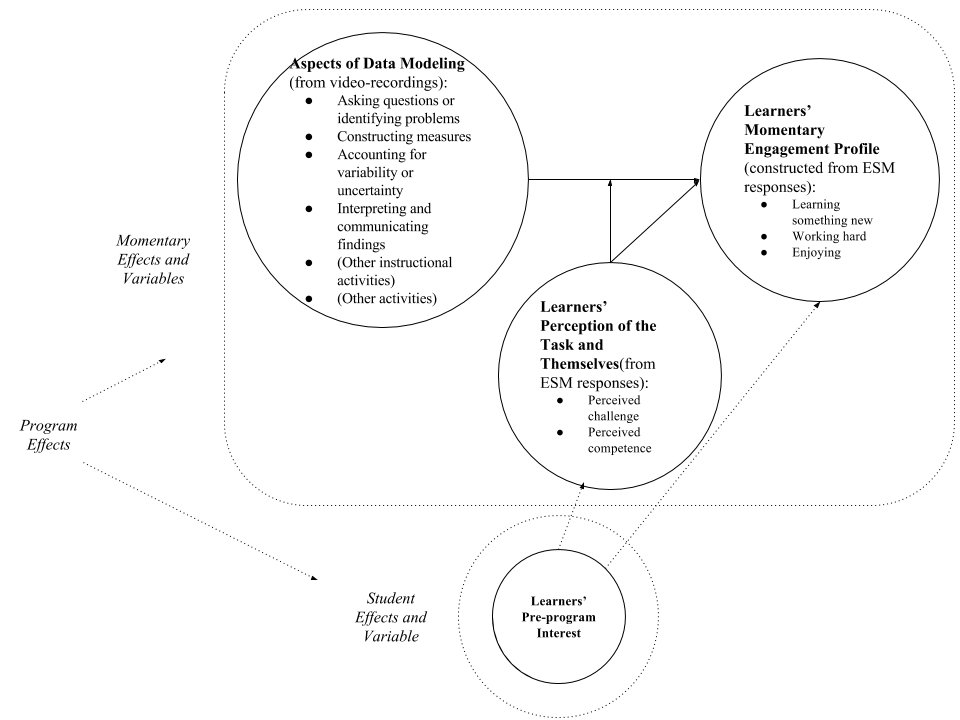
In summary of past research, this study seeks to address four specific needs. First, no research has considered data modeling in terms of learners’ engagement. Second, little research has examined how data is part of the experiences of youth in out-of-school-time programs, despite its place as one of a few core practices in STEM. Third, most studies of engagement have considered it in terms of the individual components of engagement, rather than in terms of profiles of engagement. Fourth, this study employs a data collection strategy research approach that allows for accounting for student, program, and momentary impacts on engagement.

## Conceptual Framework

The present study is about how engagement can be used to understand how learners are involved in data modeling and how characteristics of activities and learners impact the relationships between data modeling 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.

Conceptual framework in the present study.



This study is premised on the assumption that in order for students to engage in data modeling, there must be suitable conditions, in particular curricular aims that include work with data, guidance and instruction from the teacher, and access to resources. Data modeling is considered in terms of four aspects synthesized from past research (i.e., Hancock, Kaput, & Goldsmith, 1992; Lehrer & Romberg, 1996; Wild & Pfannkuch, 1999) on the process of data modeling:

1. Asking questions or identifying problems
2. Collecting and creating data
3. Accounting for variability or uncertainty
4. Interpreting and communicating findings

In this figure, how learners engage in aspects of data modeling is associated with different *momentary engagement profiles* (MEPs)*.* We know from both engagement and person-oriented research that engagement can be explained in terms of different patterns among the individual components (Bergman & Magnusson, 1997). 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 is characterized in terms of MEPs. 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, a relatively small number of MEPs can be identified in most developmental (and learning-related) settings.

In addition to understanding how learners engage in the different aspects of data modeling, knowing about how characteristics of the activity and the learner affect the relationship between data modeling and engagement is important. Influencers of engagement in data modeling, perceptions of challenge and competence, moderate the impact of opportunities to engage in data modeling on engagement (Shernoff et al., 2016). Accordingly, they are associated with both learners’ engagement and the strength of the association between the aspects of data modeling and engagement. In addition, a pre-program measure of learners’ interest in STEM is associated with both the relationship between learners’ perception of the task and themselves and data modeling and their engagement, because some learners may be inclined from the start to be more engaged.

Finally, 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 will be signaled at the same time, so 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).

## Research Questions

The research questions are as follows:

* How are the aspects of data modeling related to learners’ engagement?
* RQ 1A: How do they relate to different profiles of engagement?
* RQ 1B: How do shifts between aspects of data modeling and other activities relate to different profiles of engagement?
* How do learners’ characteristics and characteristics of activities impact how the aspects of data modeling relate to learners’ engagement?
* RQ 2A: How do learners’ perceptions of their competence impact how data modeling relates to learners’ engagement?
* RQ 2B: How do learners’ perceptions of how challenging the activity is impact how data modeling relates to learners’ engagement?
* RQ 2C: How does the interactive effect of learners’ perceptions of their competence and of how challenging the activity is impact how data modeling relates to learners’ engagement?
* RQ 2D: What are other characteristics of the activity that are common to moments that are associated with especially optimal engagement?

Answers to the first of the two questions – how are the aspects of data modeling related to learners’ engagement? – can help us to understand *how* learners engage in the different aspects of data modeling. Answers to this question can also help us to understand how learners might engage differently involved in data modeling compared to other activities. A focus on how the aspects of data modeling relate to different profiles of engagement can help us to understand whether engaging in data modeling is different from engaging in other activities. Furthermore, a focus on shifts between profiles of engagement can help us to understand when data modeling is most effective in terms of changing how learners engage.

Answers to the second of the two questions – how do learners’ characteristics and characteristics of activities impact how the aspects of data modeling relate to learners’ engagement? – can help us to understand why learners engage in different ways. Reasons for why learners engage in different ways can help us to make informed recommendations to teachers about how foster students’ data analysis efforts. Knowing about how learners’ perceptions of how challenging aspects of data modeling are and of their competence, can help us to know when and why learners find aspects of data modeling more (or less) engaging. Additionally, examining what other characteristics of the activity could impact the relationship between data modeling and learners’ engagement can help us to discover particular teaching strategies, instructional practices, and combinations of aspects of data modeling associated with engaging data modeling activities.

# Method

This is a causal comparative study, in that explanations for differences in how learners engage are sought after their occurrence. This study uses data collected as part of a study of learners’ interest and engagement in outside-of-school time STEM programs. It makes use of an exploratory sequential design, in which qualitative data is analyzed to enrich quantitative findings (Guest, 2012; Johnson, Onwuegbuzie, & Turner, 2009). In particular, while most of the analyses employ quantitative data and analyses, moments in which engagement is even greater than that expected given the values of the other variables are selected and examined qualitatively, first through an inductive step and then through a confirmatory step involving a second rater.

While programs have been video-recorded, the video have not been coded for aspects of data modeling, and the other measures from ESM and pre-survey data are to be constructed for this study.

## Participants

Participants will consist of around 204 youth. Students in these programs are from diverse racial and ethnic backgrounds. Most participants will be around 13 years old. The demographic characteristics of learners are presented in Table 1.

Table 1.

Demographic characteristics of learners.

|  |  |
| --- | --- |
| Students (*N* = 204) | % Students |
|  |  |
| Sex |  |
| Male | 50% |
| Female | 50% |
|  |  |
| Race/Ethnicity |  |
| Hispanic | 48% |
| White | 6% |
| Black | 36% |
| Multi Racial | 3% |
| Asian/Pacific Islander | 7% |
|  |  |
| Parent Education (N = 171) |  |
| High School or Below | 79% |
| Graduated from College (B.A. or B.S.) | 21% |

## 

## Context

The setting for this descriptive, exploratory study will be nine out-of-school STEM programs designed around best practices in urban areas in the Northeast United States in summer, 2015. These are described in Table 2. Program names are pseudonyms.

Table 2.

Program names and descriptions.

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

Two intermediaries, contracted by the urban area school districts to administer the summer programs, administered these 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 programs 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.

Attendance in such programs is associated with many benefits to learners (Green, Lee, Constance, & Hynes, 2012; see Lauer, Akiba, Wilkerson, Apthorp, Snow, & Martin-Glenn, 2006, for a comprehensive review). 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.

## Procedure

Students completed a pre-survey before the program. Students also completed pre- and post-course surveys of their past 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: One of the two days on each week on which data was collected was for a field experience; and one day was in the classrooms. 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 at the same time as other students within their program but at different times randomly chosen within intervals (i.e., a signal occurs at some point during a one-hour period) between programs. 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 reflection of the dynamic conceptualization of engagement, this study uses data collected from an ESM. As such, learners are to be prompted at regular intervals to respond to short questions about their perceptions of their engagement in data modeling 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.

## Data Sources and Measures

Data sources will consist of self-reported ESM measures, pre-survey measures of students’ interest, students’ demographic information, and video-recordings of programs.

Measures for engagement will be constructed from ESM responses for learning (an indicator for cognitive engagement), working hard (for behavioral engagement), and enjoying (for cognitive engagement). Measures of learners’ perceptions of the task and themselves (perceived challenge and competence) are obtained from their ESM responses completed at the same time as the ESM responses for engagement. All 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 described in Table 3.

Table 3.

ESM measures used in this study.

|  |  |
| --- | --- |
| 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?) |

Measures of students’ pre-interest are used as student-level influencers of MEPs. 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.

Pre-survey measure used in this study.

|  |  |
| --- | --- |
| 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) |

Different aspects of data modeling are identified from video-recordings with the use of a coding frame with six codes: four for each of the aspects of data modeling, 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 data modeling to other activities which are potentially engaging but not oriented toward data modeling, 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 data modeling.

|  |  |  |
| --- | --- | --- |
| Aspect of Data Modeling | Code | Description |
| Asking questions or defining problems | 0: Not Present  1: Present | Discussing topics to investigate and pose questions. |
|  |  |  |
| Collecting and creating data | 0: Not Present  1: Present | Making observations, recording data, and creating data tables and spreadsheets using analog or technological tools. |
|  |  |  |
| Analyzing and modeling data | 0: Not Present  1: Present | Summarizing, describing, and modeling data using analog or technological tools. |
|  |  |  |
| Interpreting and communicating findings | 0: Not Present  1: Present | Discussing and sharing and presenting findings. |
|  |  |  |
| Other instructional activities | 0: Not Present  1: Present | Being involved in other instructional activities: quiz and test, lecture, or video. |
|  |  |  |
| Other activities | 0: Not Present  1: Present | Being involved in non-instructional activities: off-topic time or transition between activities or program locations. |

## Data Analysis

Before analyzing data to answer RQs 1 and 2, two preliminary steps will be taken. The steps for both are described in this section.

*Preliminary analyses*

Codes for the aspects of data modeling 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 coding, inter-rater reliability between the primary and a secondary coder 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 of the codes for the aspects of data modeling. The agreement between the original and second rater will be calculated using Fleiss’ kappa, with a value above .70 indicating satisfactory agreement. If 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.

First-order Pearson correlations between, as well as the frequency, range, mean, skew, kurtosis, and standard deviations for all variables will be examined. These variables are

the ESM measures for cognitive, behavioral, and affective engagement, and for learners’ perceptions of the task and themselves, and the pre-survey measure for interest. Variables for data modeling will be included for the Pearson correlations. In addition, the frequency of the codes for data modeling, and the number of responses by student, program, and moment will be examined.

Then, to create MEPs, Latent Profile Analysis (LPA; Muthen, 2004) will be carried out. 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 Momentary Engagement Profiles (MEPs). These MEPs 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.

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; Oberski, 2016) is used in this study, in particular to identify the number and nature of MEPs. Profiles will be constructed with the three self-reported ESM measures for cognitive, behavioral, and affective engagement. Once this step is carried out, the probability of a response being associated with an MEP will be used as the dependent variable for subsequent analyses. The mclust package (Scrucca, Fop, Murphy, & Raftery, 2016) in R (R Core Team, 2017) will be used to carry out mixture modeling. The number of profiles will be determined on the basis of log-likelihood, entropy, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) statistics, and cross-validation, as well as concerns of parsimony and interpretability. The profiles will be interpreted on the basis of both the engagement-related and challenge and perceived competence measures.

*Primary analyses*

To analyze data for RQ 1 and 2, a series of mixed effects models will be carried out. In addition, a qualitative analysis will be carried out for RQ 2C. The general approach used for specifying the mixed effects is first described, followed by details about how the models will be used for providing answers to specific research questions.

All of the models will use random effects for learner, momentary, and program effect.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. 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 in two subsequent steps. First, the main effects will be added to the model with the main effects of the variables added to the null mixed effects model.

Finally, interactions between specific variables will be added as part of a bottom-up model-building process (West, Welch, & Galecki, 2014). Accordingly, these interactions will only be added when one of the two variables to be interacted is significant. The pairs variables that serve as candidates for such interactions are a) between learners’ perceptions of themselves and the task, b) between learners’ perception of themselves and any of the aspects of data modeling, c) between learners’ perceptions of the task and any of the aspects of data modeling, and d) if specified, between learners’ perception of themselves and any of the aspects of data modeling. 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. In this figure, the probability of a response being associated with an MEP (obtained through the LPA carried out during the preliminary analyses) is predicted by the direct effects of indicators for the aspects of data modeling (β01– β05 below) and learners’ perceptions of themselves and the task (β06– β07), both measured at the moment level, their pre-program STEM interest (β08), measured at the student level, and the random learner, moment, and program effects (learner, moment, and program). The general specification for the models for learner *i* during moment *j* in program *k* is:

Pr(profileijk) =

Fixed parts

00 +

01(Indicator for asking questions or identifying problems)j +

02(Indicator for collecting and creating data)j +

03(Indicator for accounting for variability or uncertainty)j +

04(Indicator for interpreting and communicating findings)j +

05(Indicator for other instructional activities)j +

06(Learners’ perception of the activity)ij +

07(Learners’ perception of themeselves)ij +

08(Learners’ pre-program STEM interest)i +

Random parts

learner(learner effect)i +

moment(moment effect)i +

program(program effect)i +

ijk

Where learnermoment, and program are assumed to ~ N(, 2)

For RQ 1A, on how the aspects of data modeling relate to different MEPs, the coefficients for indicators for five of the six aspects of data modeling will be tested to determine whether they differ significantly from zero. Coefficients greater or lesser than zero will tell us which aspects of data modeling relate to the MEP being predicted with each model, controlling for the effects of learners’ perception of themselves and the task as well as their pre-program STEM interest. In addition, these models will take account of the learner, moment, and program random effects: In other words, if specific learners, moments, or programs are more (or less) associated with an MEP, these effects will be modeled along with the predictor variables.

For RQ 1B, on how shifts between aspects of data modeling and other activities relate to different profiles of engagement, two log-linear models will be used, with the distinction being between shifts from an activity coded “1” for any of the four aspects of data modeling to an activity not coded “1” for any of the activities—from data modeling to other or non-instructional activities—and from other or non-instructional activities to data modeling. This model can help us to understand how learners’ engagement shifts, or changes, from consecutive activities that do or do not involve data modeling, helping us not only to understand whether data modeling is associated with more optimal profiles of engagement, but rather when data modeling is most effective in terms of changing how learners engage. The profile “after” (i.e., for the shift from data modeling to an other or non-instructional activity, the profile associated with the other or non-instructional activity) each shift will serve as the categorical dependent variable, with the profile “before” serving as the categorical predictor variable. Coefficients significantly different from zero will indicate shifts that occur more (or less) likely than chance, indicating how any of the data modeling is associated with changes in engagement: These particular shifts will then be presented for shifts from both data modeling to other activities and other activities to data modeling in terms of “types” (those shifts identified as occurring more likely than chance) and “anti-types” (occurring less likely than chance; Bergman et al., 2003).

For RQ 2A, on how learners’ perception of their competence impacts how data modeling relates to learners’ engagement, the indicators for the aspects of data modeling and the variable for perception of challenge will be interacted. However, as described above, these variables will only be interacted when one is significant: Specifically, if the variable for perceptions of challenge is significantly different than zero, it will be interacted with all of the indicators of data modeling, and if perceptions of challenge does not significantly differ from zero, if one of the indicators of data modeling is significantly different from zero, it will still be interacted with the variable for the perceptions of challenge.

For RQ 2B, on how learners’ perception of how challenge the activity is impacts how data modeling relates to learners’ engagement, the indicators for the aspects of data modeling and the variable for perception of challenge will be interacted. As for RQ 2A, these will be interacted only if one is significant: If the variable for perceptions of themselves is significantly different than zero, it will be interacted with all of the indicators of data modeling, and if perceptions of themself does not significantly differ from zero, if one of the indicators of data modeling is significantly different from zero, it will still be interacted with the variable for the perception of themself.

For RQ 2C, on how the interactive effect of learners’ perceptions of their competence and of how challenging the activity is relates to learners’ engagement, the interaction of these two variables and the indicators for the aspects of data modeling will be interacted. As for RQ 2A and RQ 2B, these variables will only be interacted if either the interaction between learners’ perceptions of their competence and of how challenge the activity is or one of the indicators for data modeling is significantly different from zero.

For RQ 2D, on what other characteristics of the activity could impact how data modeling relates to learners’ engagement, an Extreme Case Approach is used. In this approach, cases that demonstrate differences from the majority of the potential sample are selected, and then to develop an account of what may distinguish these from the majority, as well as what may be particular to each specific case (Jahnukainen, 2009). 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 MEPs 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. Namely, the selection process will narrow the potential cases to those associated with especially optimal engagement. In particular, these moments will be identified only for those moments coded for one of the four aspects of data modeling through the selection of those moments with random effects (moment) above the 80th percentile from the final models, or those with not only the direct effects of the variables but also those with the addition of any interactions among the variables. These moments will therefore be those that systematically exhibit higher probabilities of responses associated with the different MEPs, controlling for the effects of all of the predictor variables and accounting for the variability and number of the responses associated with the moments. Qualitative analyses will be carried out in two steps.

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 data modeling presented in Figure 1: phenomena-based investigations, reference to or the presence of repeated cycles of data modeling 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 aspects of data modeling 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 .70 indicating satisfactory agreement. If disagreement 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 data modeling will be sampled from) will be coded again.

# References

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. (2015). Epistemologies in practice: Making scientific practices meaningful for students. *Journal of Research in Science Teaching.*

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.

Collins, A. (2017). What's Worth Teaching? Rethinking Curriculum in the Age of Technology. New York, NY: Teachers College Press.

Common Core State Standards Initiative. (2010). *Common Core State Standards for Mathematics (CCSSM).* 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. Basic Books.

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.* 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 Handbook of research on student engagement (pp. 763-782). Springer US.

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.*

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

Johnston, A. M., Sheskin, M., Johnson, S. G., & Keil, F. C. (2017). Preferences for Explanation Generality Develop Early in Biology But Not Physics. *Child Development*.

Konold, C., & Pollatsek, A. (2002). Data analysis as the search for signals in noisy processes. *Journal for Research in Mathematics Education*, 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., & Tran, D. (2015). *Describing the SASI framework.* In Teaching statistics through data investigations MOOC-Ed, Friday Institute for Educational Innovation: NC State University, Raleigh, NC. Retrieved from [http://info.mooc-ed.org.s3.amazonaws.com/tsdi1/Unit%203/Unit%203/SASI%20Framework.pdf](http://info.mooc-ed.org.s3.amazonaws.com/tsdi1/Unit%203/Unit%203/SASI%20Framework.pdf" \t "_blank)

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). *The development of scientific thinking.* Handbook of Child Psychology and Developmental Science.

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. (Eds.). (2012). *Thinking with data.* Psychology Press.

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

McNeill, K. L., & Berland, L. (2016). What is (or should be) scientific evidence use in k‐12 classrooms?. *Journal of Research in Science Teaching.*

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

Nemirovsky, R., Kaput, J. J., & Roschelle, J. (1998). *Enlarging mathematical activity from modeling phenomena to generating phenomena*. In PME CONFERENCE (Vol. 3, pp. 3-287).

NGSS Lead States. (2013). Next generation science standards: For states, by states. National Academies Press.

Nolen, S. B., Horn, I. S., & Ward, C. J. (2015). Situating motivation. *Educational Psychologist, 50*(3), 234-247.

Oberski, D. (2016). Mixture models: Latent profile and latent class analysis. In *Modern Statistical Methods for HCI* (pp. 275-287). Springer International Publishing.

Online at <http://www.amstat.org/education/gaise/>.

Petrosino, A. (2003). Commentary: A framework for supporting learning and teaching about mathematical and scientific models. *Contemporary Issues in Technology and Teacher Education, 3*(3), 288-299.

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*. Basic books.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Raudenbush, S. W., & Bryk, A. S. (2002). Hierarchical linear models: Applications and data analysis methods (2nd ed.). Thousand Oaks, CA: Sage.

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. (in press). A person-in-context approach to student engagement in science: Examining learning activities and choice. *Journal of Research in Science Teaching.*

Schwarz, N., Kahneman, D., Xu, J., Belli, R., Stafford, F., & Alwin, D. (2009). Global and episodic reports of hedonic experience. *Using calendar and diary methods in life events research*, 157-174. SAGE.

Scrucca, L., Fop, M., Murphy, T. B., & Raftery, A. E. (2016). mclust 5: Clustering, classification and density estimation using Gaussian finite mixture models. *The R Journal, 8*(1), 289.

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.

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, L. B., & Thelen, E. (2003). Development as a dynamic system. *Trends in cognitive sciences, 7(*8), 343-348.

statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

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.

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.

Tukey, J. W. (1962). The future of data analysis. *The Annals of Mathematical Statistics, 33*(1), 1-67.

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.

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.

Wang, M. T., Fredricks, J. A., Ye, F., Hofkens, T. L., & Linn, J. S. (2016). The Math and Science Engagement Scales: Scale development, validation, and psychometric properties. *Learning and Instruction, 43*, 16-26.

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.

Wormington, S. V., & Linnenbrink-Garcia, L. (2016). A new look at multiple goal pursuit: The promise of a person-centered approach. *Educational Psychology Review*, 1-39.

## 