Examining Data Practices Through the Lens of Engagement Theory:

A Person-Oriented Approach Using an Experience Sampling Method

By Joshua M. Rosenberg

Michigan State University

A Dissertation Proposal

Proposed: 9/7/2017

Revised: 10/9/2017

Table of Contents

Literature Review 6

Defining Data Analysis and the Role of Data Modeling 6

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

Engagement in STEM Domains 14

Using ESM to Study the Dynamics of Engagement 17

A Person-Oriented Approach to Engagement 19

Need for the Present Study 22

Conceptual Framework 22

Research Questions 24

Method 25

Participants 26

Context 27

Procedure 30

Data Sources and Measures 31

Data Analysis 34

Power Analysis 41

Limitations 41

Significance 42

References 43

Abstract

This study will examine how 203 early adolescent learners engage in data practices, 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 data practices: asking questions or identifying problems, constructing measures, collecting data, accounting for variability or uncertainty, and interpreting and communicating findings. 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 data practices. Examining data practices 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 engagement in data practices. Knowing more about students’ engagement can help us to design activities and interventions around data practices that are highly engaging to students and that support their capabilities to work with data.

Examining Data Practices Through the Lens of Engagement Theory:

A Person-Oriented Approach Using an Experience Sampling Method

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 data practices 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 data practices 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. Engagement in data practices 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).

# 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 practices 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.

## Defining Data Practices

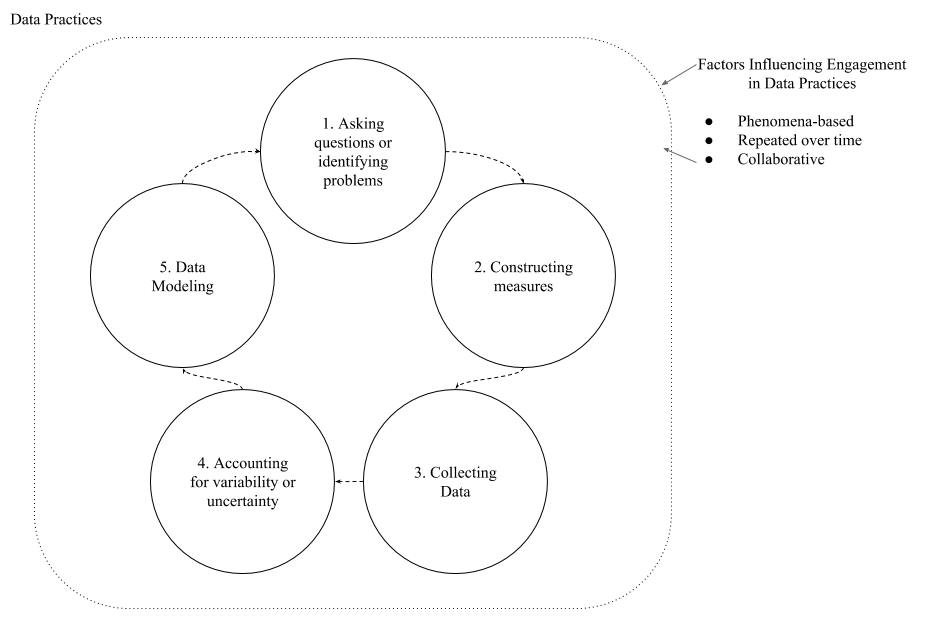
As described in the introduction to this section, some scholars have focused on a few key pieces of data analysis connected through the use of “data to solve real problems and to answer authentic questions” (Hancock et al., 1992, p. 337). This approach is commonly described as including two goals, 1) 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 data practices 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 data practices 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 data practices**.The definition of engaging in data practices 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 data practices, 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, constructing measures of phenomena, collecting data, data modeling, 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 data practices. The first process, asking questions, is about generating questions that can be answered with empirical evidence. The next, constructing measures of phenomena, is about identifying potential sources of data and ways to measure them. This is followed by collecting data, the process of transforming observations into data through the use of measures. 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*. Engagement in data practices and the factors influencing it.



Also, as depicted in Figure 1, scholars have pointed out some key features of how data practices are 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 data practices 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 data practices in the curriculum**.Scholars argue that engagement in data practices 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 data practices 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 data practices 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 data practices, 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.

The data practices are 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, data practices 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 data practices 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 data practices 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 data practices. Therefore, these programs can provide insight into whether engaging in data practices is associated with more optimal forms of engagement in the conditions like those for classrooms in which engaging in data practices is a novel and potentially promising approach to doing and learning about STEM.

## What We Know (And Do Not Know) About Engagement in Data Practices

Research related to engagement in data practices 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 data practices
3. Strategies to address key challenges of engaging in data practices

First, scholars have researched cognitive capabilities related to the data practices. 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 data practices 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 data practices (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 data practices 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 data practices 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 data practices in a better-supported way that is sustained over time.

Third, strategies to support engagement in data practices 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 data practices, 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 data practices 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).

## 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 data practices are most engaging (and in what ways), and therefore can serve as exemplary for others advancing data practices, 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.

Consequently, this study considers not only profiles of engagement, but also the conditions of engagement as part of the profiles. 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. These conditions are different from those discussed in the section on the five data practices in that they are subjective factors, 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.

## 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, Schmidt, & Maier, 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 data practices. 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.

## 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 data practices 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.