How Youth Experience Work With Data in Summer STEM Programs: Findings From An Experience Sampling Approach

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Abstract

Working with data – forming questions, constructing measures and attending to precision, and creating models and representations of data, for example –can serve as a context for learning across STEM content areas. Furthermore, becoming proficient in work with data can be personally empowering because of the parts of our lives–from paying energy bills to interpreting news articles–that use data. While there has been research on work with data in mathematics content areas, less has focused on such practices in science and engineering educational settings. The present study explores learners’ engagement in work with data in the context of nine summer STEM programs. Data from measures of learners’ engagement was collected through the Experience Sampling Method (ESM) and was collected from more than 200 youth in nine summer STEM programs over four weeks in the Northeastern United States. Findings show that aspects of work with data were fairly common in the programs overall. Six profiles of youth engagement were identified, representing distinct configurations of the five indicators of engagement. Relations between the profiles of engagement and each of the aspects of work with data were small: Notable exceptions were the generating data and data modeling were significantly associated with full engagement. Youth with higher pre-program interest in STEM were more likely to be engaged and competent but not challenged, though other youth characteristics were not highly related to the profiles. Implications of the findings and the implications for practice with respect to work with data in general and to engagement in informal learning environments, such as summer STEM programs, in both cases with an emphasis on how work with data can serve as a promising context for learning in STEM subject areas.

*Keywords:* Work with data, data science education, experience sampling method, engagement, out-of-school STEM programs

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Today, data are all around us, shaping how we work, socialize, teach, and learn. Data are not only ubiquitous but are also important. In education, administrators use data to make decisions about the quality of teachers (McCaffrey, Lockwood, Koretz, & Hamilton, 2003) and teachers about students (Horn, Kane, & Wilson, 2015). While there has been a lot of attention in higher and K-12 education on the roles that data in its many forms has, we have not considered exactly what the relationship between learners and data—created by them, provided to them, or used to assess them—ought to be.

Though there has been research about students’ engagement in math and science (Fredricks, Filsecker, & Lawson, 2016; Schmidt, Rosenberg, & Beymer, 2018; Schneider et al., 2016), research has not examined how students engage in work with data. Knowing more about how youth engage in work with data is valuable as engagement is a meaningful outcome for STEM learners in its own right (Sinatra, Heddy, & Lombardi, 2015). It may also be an antecedent of changes in other outcomes, such as their well-being, achievement, and the pursuit of an area of study or career (Wang & Eccles, 2012). Because engaging in work with data seems to be so potentially beneficial to learners, better understanding the nature of work with data and learners’ engagement in such practices is needed.

The purpose of this study, then, is to examine youth engagement in a variety of learning activities that involve work with data. We explore youths’ engagement in the context of outside-of-school STEM enrichment programs carried out during the summer. Such settings are an especially useful context for exploring work with data because they can be designed around youths’ interests (Lauer, Akiba, Wilkerson, Apthorp, Snow, & Martin-Glenn, 2006). One promise of work with data in outside-of-school settings is that relevant sources of data can be inherently interesting to learners. Such sources of data can be used as a context for learning about the world, allowing youth to ask and answer personally and socially meaningful questions, whereas many outside-of-school programs are focused around commercial aims, such as developing mobile device applications. Knowing more about how youth engage can also provide a foundation for subsequent work to explore how particular curricula and engaging experiences for youth spark their interest in work with data, including hobbies and occupations related to data science, but also in STEM domains in general.

# Defining Work with Data

Work with data has been conceived in different ways (i.e., Hancock et al., 1992; Lehrer & Romberg, 1996; Wild & Pfannkuch, 1999). 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 and is instantiated in standards for some (especially mathematics) curricula. Franklin et al.’s guidelines 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 et al. (1992) focus in on two goals, data creation and analysis, arguing that the former (data creation) is under emphasized in classroom contexts. 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 applied to the task of understanding plant growth). The last of these components is crucial across all of the visions of data modeling 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.

Because there is not an agreed-upon definition of work with data–particularly across subject area domains (i.e., across all of the STEM content areas)–WE focus on the core aspects that scholars have most often included in their conceptualizations of work with data. These core components, synthesized from definitions across studies, are better for understanding work with data across STEM content areas–as in the present study–than the components from specific examples, which were developed for use in only one domain. The aspects of work with data that have been articulated in prior studies are distilled into five key aspects for use in this study. They are:

* *Asking questions*: Generating questions that can be answered with empirical evidence
* *Making observations*: Watching phenomena and noticing what is happening concerning the phenomena or problem being investigated
* *Generating data*: The process of figuring out how or why to inscribe an observation as data about phenomena, as well as generating tools for measuring or categorizing
* *Data modeling*: Activities involving the use of simple statistics, such as the mean and standard deviation, as well as more complicated models, such as linear models and extensions of the linear model
* *Interpreting and communicating findings*: Activities related to identifying a driving question regarding the phenomena that the question is about

These aspects of work with data are not stand-alone practices but are a part of an iterative cycle. For example, interpreting findings leads to new questions and subsequent engagement in work with data. Also, scholars have pointed out some key features of how work with data is carried out that impact their effectiveness as a pedagogical approach. These key features include an emphasis on making sense of real-world phenomena and iterative cycles of engaging in work with data and collaboration and dialogue, through which ideas and findings are critiqued and subject to critique, and revised over time (McNeill & Berland, 2017; Lee & Wilkerson, 2018).

# What is Known About How Youth Work with Data

Working with data is more than just crunching numbers or interpreting a figure created by someone else. It refers to a number of broad processes aimed at making sense of phenomena or solving problems in the world. This focus on phenomena is particularly relevant to those designing and enacting learning opportunities focused on work with data given the greater availability (or the ability to create data about) many aspects of the natural and social world (Lee & Wilkerson, 2018). These capabilities may be particularly useful in STEM domains because advanced coursework in these domains often involves demanding and abstract work with data, work that may be more accessible to more learners when they encounter it earlier in their education.

Past research on work with data has mostly been set in mathematics contexts and has focused on mathematical practices, like generating measures of phenomena and creating data models (English, 2012; Lehrer & Romberg, 1996; Lesh, Middleton, Caylor, & Gupta, 2008). It has often focused on specific cognitive outcomes (e.g., Gelman & Markman, 1987), strategies to support work with data (Petrosino, Lehrer, & Schauble, 2003), and some opportunities and challenges facing both teachers and learners when working with data (e.g., Konold & Pollatsek, 2002; Finzer, 2013). There has been some research about work with data in science settings, too. However, what it means to work with data can vary greatly in actual classrooms and other learning environments (McNeill & Berland, 2017).

There is a good amount of past research on cognitive capabilities as outcomes from working with data. Much of this—laboratory-based—research has focused on how children develop the capability to inductively reason from observations (Gelman & Markman, 1987). Other research has focused on the development of causal, or mechanistic, reasoning, among young children (Gopnik & Sobel, 2000; Gopnik, Sobel, Schulz, & Glymour, 2001). A key outcome of engaging in work with data has to do with how learners account for variability (Lehrer, Kim, & Schauble, 2007; Petrosino et al., 2003; Lesh, Middleton, Caylor, & Gupta, 2008; Lee, Angotti, & Tarr, 2010), arguably the main goal of engaging in work with data (Konold & Pollatsek, 2002). From this research, we know that learners can develop the capacity to reason about variability.

Past research has also shown that there are strategies that can support work with data. These include the design of technological tools and the development of curricula. From this research, we know about specific strategies and learning progressions for learners to develop this capability. For example, past research has illustrated the role of measurement in exposing learners in a direct way to sources of variability (Petrosino et al., 2003) or the place of relevant phenomena, such as manufacturing processes, such as the size of metallic bolts, which can help learners to focus on “tracking a process by looking at its output” (Konold & Pollatsek, 2002, p. 282).

Finally, past research has shown that different aspects of work with data pose unique opportunities and challenges. Asking empirical questions requires experience and ample time to ask a question that is both able to be answered with data and which is sustaining and worth investigating (Bielik & Yarden, 2016; Hasson & Yarden, 2012). Making observations and generating data, such as of the height of the school’s flagpole, requires negotiation not only of what to measure, but how and how many times to measure it (Lehrer, Kim, & Schauble, 2007). Regarding modeling, not only teaching students about models, such as that of the mean, but also asking them to create them, are valuable and practical (Lehrer & Schauble, 2004; Lehrer, Kim, & Jones, 2011), but also time-intensive. Interpreting findings, especially in light of variability through models, and communicating answers to questions, means not only identifying error but understanding its sources, and can be supported through exploring models that deliberately represent the data poorly, but can be instructive for probing the benefits and weaknesses of models (Konold & Pollatsek, 2002; Lee & Hollebrands, 2008; Lehrer, Kim, & Schauble, 2007).

Though this valuable past research has been carried out, valuable insight into how learners and youth participate in different aspects of work with data through the lens of engagement has not been explored. Consider the practice of modeling data, commonly described as a-or *the*-key part of many data analyses (Konold, Finzer, & Kreetong, 2017): When modeling data, learners may use data they generated and structured in a data set on their own or may model already-processed, or use already-plotted, data (McNeill & Berland, 2017). How challenging do students perceive the different enactments of these activities to be and how do learners perceive their competence regarding them? Importantly, how hard are learners working? How much do they feel they are learning? Knowing more about these beliefs, characteristics, and processes could help us to develop informed recommendations for teachers and designers intending to bring about opportunities for learners to engage in work with data in a better-supported way that is sustained over time.

**Engagement in General and in STEM Content Areas**

Engagement is defined in this study as active involvement, or investment, in activities (Fredricks, Blumenfeld, & Paris, 2004). Explaining how learners are involved in activities and tasks is especially important if we want to know about what aspects of work with data are most engaging (and in what ways), and therefore can serve as examples for others advancing work with data as well as those calling for greater support for engagement. Apart from being focused on involvement, engagement is often thought of as a meta-construct, that is, one that is made up of other constructs (Skinner & Pitzer, 2012; Skinner, Kindermann, & Furrer, 2009). By defining engagement as a meta-construct, scholars characterize it in terms of cognitive, behavioral, and affective dimensions that are distinct yet interrelated (Fredricks, 2016).

We know from past research that the cognitive, behavioral, and affective dimensions of engagement can be distinguished (Wang & Eccles, 2012; Wang & Holcombe, 2010) and that while there are long-standing concerns about the conceptual breadth of engagement (Fredricks et al., 2016), careful justification and thoughtful use of multidimensional engagement constructs and measures is warranted. Engagement is also considered to be changing in response to individual, situation or moment contextual factors, Skinner and Pitzer's (2012) model of motivational dynamics, highlighting the community, school, classroom, and even learning activity, shows the context-dependent nature of engagement on the basis of the impacts of these factors on learners' engagement.

Engagement in STEM settings shares characteristics with engagement across disciplines, yet there are some distinct aspects to it (Greene, 2015). For example, many scholars have defined scientific and engineering practices as cognitive practices, which involve applying epistemic considerations around sources of evidence and the nature of explanatory processes (Berland et al. 201). The emphasis on developing new knowledge and capabilities by engaging in STEM practices must be reflected in how the cognitive dimension of engagement is measured. Because of the importance of constructing knowledge to engagement in STEM practices, then. While sometimes defined in terms of extra-curricular involvement or following directions, behavioral engagement can be considered working hard on learning-related activities (Fredricks et al., 2004; Singh, Granville, & Dika, 2002). Finally, affective engagement can be defined as emotional responses to activities, such as being excited, angry, or relaxed (Pekrun & Linnenbrink-Garcia, 2012).

Also, some critical conditions facilitate engagement. Emergent Motivation Theory (EMT; Csikszentmihalyi, 1990), provides a useful lens for understanding these conditions. From EMT, a critical condition for engagement that can change dynamically, from moment to moment, is how difficult individuals perceive an activity to be, or its perceived challenge. Another critical condition is how good at an activity an individual perceives themselves to be, or their perceived competence. What is most important--and necessary concerning being engaged--is being both challenged by and good at a particular activity, past research has found (Shernoff et al., 2016). Conceptualizing perceptions of challenge and competence as conditions, rather than factors that influence engagement, can be a recognition of their co-occurrence within individuals, in that youth experience engagement and their perceptions of the activity (perceived challenge) and of themselves (perceive competence) together and at the same time. Thus, these two conditions can be considered together with engagement, as in this the present study.

**Youth Characteristics That May Affect Their Engagement**

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

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

**The Challenge of Studying Engagement**

Because of the way engagement has been thought of as having context-dependent characteristics and being multi-dimensional, it is challenging to use engagement (when conceptualized in such a way) in empirical studies. One methodological approach that has benefits concerning the context-dependent and multidimensional nature of engagement is the ESM. Some scholars have explored or extolled benefits to its use in their recent work (e.g., Strati et al., 2017; Turner & Meyer, 2000; Sinatra et al., 2015). This study employs the Experience Sampling Method (ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007) where learners answer short questions about their experience when signaled. ESM involves asking (usually using a digital tool and occasionally a diary) participants short questions about their experiences. ESM is particularly well-suited to understanding the context-dependent nature of engagement because students answered brief surveys about their experience when they were signaled, minimally interrupting them from the activity they are engaged in and also seeking to collect measures about learners’ experience when signaled (Hektner et al., 2007). The ESM approach is both sensitive to changes in engagement over time, as well as between learners and allows us to understand engagement and how factors impact it in more nuanced and complex ways (Turner & Meyer, 2000). Though time-consuming to carry out, ESM can be a robust 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).

One powerful and increasingly widely used way to examine context-dependent constructs, such as engagement, is the use of profiles of, or groups of variables that are measured. This profile approach is especially important given the multidimensional nature of engagement. In past research, profiles are commonly used as part of what is described as person-oriented approaches (Bergman & Magnusson, 1997; Bergman, Magnusson, & El Khouri, 2003), those used to consider the way in which psychological constructs are experienced together and at once in the experiences of learners. There are some recent studies taking a profile approach to the study of engagement (i.e., Salmela-Aro, Moeller, Schneider, Spicer, & Lavonen, 2016a; Salmela-Aro, Muotka, Alho, Hakkarainen, & Lonka, 2016b; Van Rooij, Jansen, & van de Grift, 2017; Schmidt, Rosenberg, & Beymer, 2018), though none have done so to study youths' engagement in work with data.

The profile approach has an important implication for how we analyze data collected from ESM about youths' engagement, in particular when we consider how to understand engagement as a multi-dimensional construct, and one with momentary, or instructional episode-specific, conditions (Csikszentmihalyi, 1990). We know from past research that engagement can be explained through different patterns among its individual dimensions (Bergman & Magnusson, 1997; Bergman et al., 2003). 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.

Some past studies have considered profiles of cognitive, behavioral, and affective aspects of engagement (i.e., Salmela-Aro et al., 2016b; Schmidt et al., 2018). A potential way to extend this past research is to account for not only engagement (cognitive, behavioral, and affective), but also the intricately connected perceptions of challenge and competence. This analytic approach is especially important since a profile approach emphasizes the holistic nature of engagement and the impact of not only external but also intra-individual factors. Thus, the profiles of engagement may usefully include not only the dimensions of engagement, but also youths’ perceptions of how challenging the activity they were doing is and of how competent at the activity they are.

## Need for the Present Study

While many scholars have argued that work with data can be understood in terms of the capabilities learners develop and the outcome learners achieve, there is a need to understand learners’ experiences working with data. The present study does this in terms of contemporary engagement theory (Fredricks, Blumenfeld, & Paris, 2014). Doing this can help us to understand work with data in terms of learner’s engagement, which we know from past research impacts what and how students learn (Sinatra et al., 2015). Knowing more about students’ engagement can help us to design activities and interventions focused around work with data. In particular, an Experience Sampling Method (ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007) approach may be useful for measuring youths’ engagement not before or after their experiences, but rather during the specific activities that involve work with data. In addition to this need to study learners’ experience working work with data through the lens of engagement theory, no research has yet examined work with data in the context of summer STEM programs, though such settings are potentially rich with opportunities for highly engaged youth to analyze authentic data sources.

## Conceptual Framework and Research Questions

To summarize in Figure 1, engagement in work with data is associated with different profiles of engagement. The theoretical framework for the profile approach suggests that engagement is a multi-dimensional construct consisting of cognitive, behavioral, and affective dimensions of engagement and perceptions of challenge and competence. The five aspects of work with data and youths’ pre-program interest, gender, and URM status are predictor variables at the youth level.

The four research questions, then, are:

1. How frequent is work with data in summer STEM programs?
2. What profiles of engagement emerge from data collected via ESM in the programs?
3. How does work with data relate to the profiles of engagement?
4. How do youth characteristics relate to profiles of engagement?

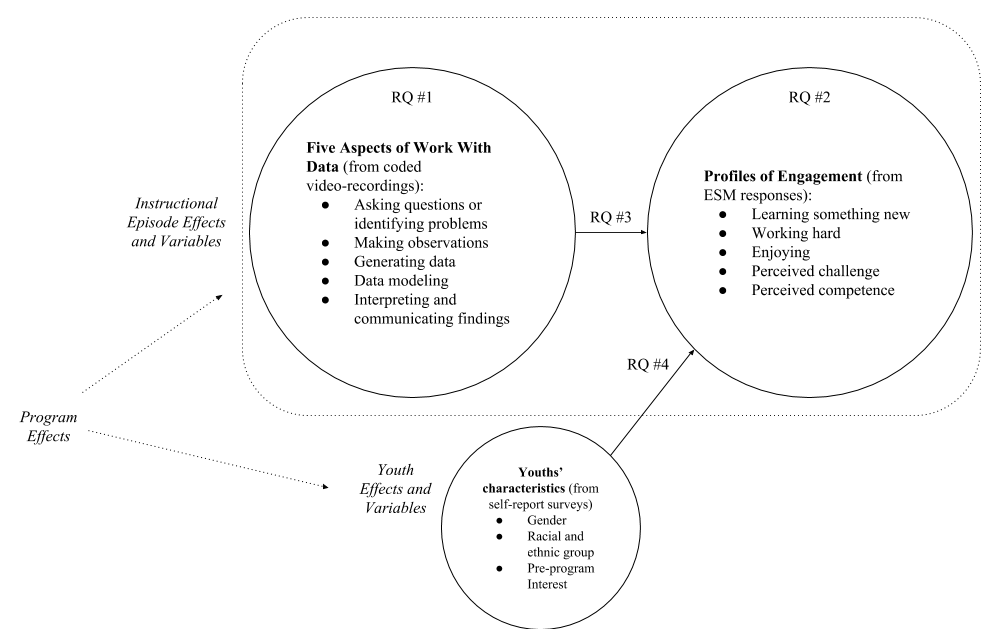


Figure 1. A conceptual framework for this study and research questions.

# Method

In this section, we describe the context and participants, followed by the procedure, measures and their associated data sources, and the data analyses necessary to answer each of the research questions.

## Context

The setting for the present study was nine out-of-school STEM programs in the Northeastern United States during 2015. Youth spent around three hours per day for four days per week for the approximately four-week programs, which were taught by youth activity leaders and scientists, engineers, and other community members with technical expertise. As can be seen in the descriptions of the programs provided in Supplementary Materials A, many of the programs aimed to involve youth in work with data.

## Participants

The participants were 203 youth. Participants were from diverse racial and ethnic backgrounds (see Table 1). The mean age of participants was around 13 years old (*M* = 12.71, *SD* = 1.70, *min.* = 10.75, *max.* = 16.36).

Table 1. Demographic characteristics for participating youth.

|  |  |
| --- | --- |
| Youth | Percentage |
| Sex | NA |
| Male | 50 |
| Female | 50 |
| Race/Ethnicity | NA |
| Hispanic | 48 |
| White | 6 |
| Black | 36 |
| Multi-racial | 3 |
| Asian/Pacific Islander | 7 |
| Parent Education | NA |
| High School or Below | 79 |
| Graduated from College (B.A. or B.S.) | 21 |

## Procedure

Before the beginning of the programs, youth completed a pre-survey that included questions about their experience in STEM, intention to pursue a STEM major or career, and other motivation and engagement-related measures; items about youths’ interest in STEM were the only items used from this survey in this study.

At the programs’ beginning, youth were introduced to the ESM data collection method. ESM is a method of data collection that involves asking youth to respond to short questions in the context of their daily lives, rather than before or after particular activities—or, in school, before or after a unit or even an entire year (Schmidt, & Csikszentmihalyi, 2007). In this instantiation of ESM, youth were signaled at random times (within intervals, so that the signals were not too near or far apart) to respond to short questions on phones that were provided to youth as a part of the study. ESM data were collected two days each week, for three weeks (weeks 2-4 of the program). Each day, youth were signaled four times[[1]](#footnote-1).

In addition to the collection of ESM data during the programs, video data were collected, as well. In all of the programs, about equal video-recording time was dedicated to classroom and field experiences. Video-recording was carried out by research team members on the days during which ESM data were collected. So that the measures relating the video-recording and ESM data can be matched, the videos included a signal from the person doing the video-recording that identified the ESM signal to which youth were signaled to respond.

Demographic information about youth were collected from the programs.

## Data Sources and Measures

Data sources come from the pre-program survey, ESM, video-recordings, and demographic information.

### ESM measures of engagement for the profiles

. Measures for engagement were created from five short ESM questions (Table 2). Each of the ESM items consisted of the item text and the following four item response options, of which youth were directed to select one: Not at all (associated with the number 1 on the survey; 1), A little (2), Somewhat (3), and Very Much (4).

Table 2. Items for constructs measured through ESM

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

### Measures from video for work with data

### Codes for work with data were generated on the basis of the activity that the youth activity leaders were facilitating. The activity youth activity leaders were facilitating were from the STEM-Program Quality Assessment (STEM-PQA; Forum for Youth Investment, 2012), an assessment of quality programming in after-school programs. The five aspects of work with data were identified through codes from the STEM-PQA[[2]](#footnote-2), which was designed to describe the types of activities the program leaders were facilitating, as operationalized in Table 3.

Table 3. Codes for the aspects of work with data.

|  |  |  |  |
| --- | --- | --- | --- |
| Code Name | Values | Description | Example |
| Asking questions | 1: Present; 0: Not Present | Discussing and exploring topics to investigate and pose questions. | Youth generated questions they investigated related to tide ponds in an estuary ecosystem. |
| Making observations | 1: Present; 0: Not Present | Watching and noticing what is happening with respect to the phenomena or problem being investigated. | Youth observed the projectile motion of an object launched with a catapult. |
| Generating data | 1: Present; 0: Not Present | Figuring out how or why to inscribe an observation as data and generating coding frames or measurement tools. | Youth wrote in a table the number of pieces of recyclables they collected in parts of local waterways. |
| Data modeling | 1: Present; 0: Not Present | Understanding and explaining phenomena using models of the data that account for variability or uncertainty. | Youth calculated the average number of plant species found across a number of sites in the field. |
| Interpreting and communicating findings | 1: Present; 0: Not Present | Discussing and sharing findings. | Youth presented the outcomes of an investigation or engineered design in light of a research question or problem. |

Raters contracted by American Institute of Research (AIR) were trained in the use of the Program Quality Assessment tool (PQA), the broader assessment tool for which the STEM-PQA is a supplement. For the STEM-PQA, three of the same raters contracted by AIR to code the overall PQA measure used the STEM-PQA supplement to score one video segment, for which there were no disagreements on scoring for any of the items. The programs were divided up among all of the raters, so raters coded some of the videos for all of the programs. When the raters encountered a situation that was difficult to score, they would discuss the issue by telephone or more often by email after viewing the video in question and reach a consensus on how to score the specific item. Out of the 248 instructional episodes, 236 were code-able for work with data; for the 12 that were not codeable, issues with the video-recordings were the primary source of the missing data. These 236 responses were used for all of the analyses.

### Survey measures of pre-interest in STEM

. Three items adapted from Vandell, Hall, O’Cadiz, and Karsh (2012) were used to measure youths’ pre-program interest in STEM[[3]](#footnote-3). Like the ESM measures, youth were asked to report their agreement with the three items on a 1 (A little) to 4 (Very much) scale. Reliability and validity information on this scale is presented in Vandell et al. (2008). The three items were: 1) I am interested in science / mathematics / engineering; 2) At school, science / mathematics / engineering is fun; 3) I have always been fascinated by science / mathematics / engineering).

### Demographic measures

. Demographic information for youths’ gender, and their racial and ethnic group were used to construct demographic variables for gender and membership in an under-represented (in STEM) group; membership in an under-represented group was identified on the basis of youths’ racial and ethnic group being Hispanic, African American, or native American.

## Data Analysis

**Preliminary analyses**. Correlations (first-order Pearson) and the frequency, range, mean (*M*), and standard deviation (*SD*) are first reported for all variables. In addition, the frequencies of the codes for aspects of work with data and the numbers of responses by youth, program, and instructional episode are presented.

### Analysis for Research Question #1 (the frequency of work with data)

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The codes for the aspects of work with data (described above in the section on the measures) were counted and presented as a proportion of the number of code-able instructional episodes. Results from this analysis provide initial insight into how often each of the aspects took place during the programs.

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

. Latent Profile Analysis (LPA; Harring & Hodis, 2016; Muthen, 2004) were used to identify profiles of engagement. A key benefit of the use of LPA is that it outputs the probability of an observation being a member of a cluster (unlike in cluster analysis). For these analyses, five variables were included: the three indicators for the experience of engagement (cognitive, behavioral, and affective) and the two necessary conditions for it (perceptions of challenge and competence). In addition, solutions with between two and ten profiles were considered. As part of LPA, the model type selection-where the type refers to which parameters are estimated–is a crucial topic. For the present study, six model types were considered. The tidyLPA package (Authors, 2018) and the MPlus software (Muthen & Muthen, 1998-2017) was used to carry out LPA through open-source statistical software we developed.

To select a solution in terms of the model type and the number of profiles to be interpreted and used in subsequent analyses, a number of fit statistics and other considerations were taken into account. These include a range of information criteria (AIC, BIC, and sample adjusted BIC [SABIC]), statistics about the quality of the profile assignments (entropy, which represents the mean posterior probability), a statistical test (the bootstrapped LRT [BLRT]), and concerns of interpretability and parsimony. On the basis of these criteria, a particular solution was selected and used as part of subsequent analyses.

### Analysis for Research Question #3 (how work with data relate to engagement) and Research Question #4 (how youth characteristics relate to engagement)

For this question, mixed effects models that account for the cross-classification of the instructional episode (because of the dependencies of the responses associated with each of the 248 distinct ESM signals) and youth are used and for the “nesting” of both within each of the nine programs are used. The *lme4* R package (Bates, Martin, Bolker, & Walker, 2015) was used. All of the models for this and the subsequent research question use random effects for youth, instructional episode, and program effects[[4]](#footnote-4). The probability of a response belonging to the profile was the dependent variable, and the aspects of work with data are the independent variables.

The results are interpreted in terms statistical significance and the magnitude and direction of the coefficients: For example, if the coefficient for the effect of the asking questions aspect of work with data upon one of the profiles was 0.10, and is determined to be statistically significant, then this would indicate that when youth are engaged in this aspect of work with data, then they are ten percentage points more likely to report a response in that particular profile.

For this question, models with the aspects of work with data both separate from and together with the youth characteristics were fit. The models with both sets together were also used as part of research question #4, though they are presented here (and interpreted in the sections for both results). Because the results were found to be identical when the aspects of work with data and the youth characteristics were considered in separate and in the same model, the results from the two sets of variables being in the same model were used both to provide answers to both this and the next research question. Specifically, pre-program interest in STEM, gender and URM status were added as predictors along with the aspects of work with data.

# Results

## Descriptive statistics for the engagement measures

First, descriptive statistics for the five engagement variables that were used to estimate the profiles were calculated.These descriptive statistics show high overall levels of cognitive (*M* = 2.768, *SD* = 1.063), behavioral (*M* = 2.863, *SD* = 1.044) and affective (*M* = 2.831, *SD* = 1.051) engagement. These statistics also show high perceptions of competence (*M* = 3.000 (*SD* = 0.952)) and moderate perceptions of challenge (*M* = 2.270 (*SD* = 1.117)).

## Correlations among the study variables

Correlations between the variables that were used to create the profiles of engagement and the one other variable which was continuous (rather than a code for groups, in particular youths’ gender and URM status), pre-program interest in STEM (Table 4), were specified. In addition, relations between these variables and those for the five aspects of work with data were identified.

Table 4. Bivariate correlations among the study variables

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Pre-interest | Cog. eng. | Beh. eng. | Aff. eng. | Chall. | Comp. | Ask. | Obs. | Gen. | Mod. | Com. |
| Pre-interest |  |  |  |  |  |  |  |  |  |  |  |
| Cog. eng. | .14 |  |  |  |  |  |  |  |  |  |  |
| Beh. eng. | .13 | .60 |  |  |  |  |  |  |  |  |  |
| Aff. eng. | .12 | .59 | .57 |  |  |  |  |  |  |  |  |
| Chall. | .15 | .30 | .27 | .27 |  |  |  |  |  |  |  |
| Comp. | .06 | .40 | .41 | .47 | .08 |  |  |  |  |  |  |
| Ask. | -.18 | .02 | .01 | .01 | -.01 | -.01 |  |  |  |  |  |
| Obs. | .11 | .01 | .03 | -.01 | -.02 | -.00 | .38 |  |  |  |  |
| Gen. | -.08 | .02 | .02 | -.03 | -.01 | -.05 | .31 | .30 |  |  |  |
| Mod. | -.03 | .02 | .01 | .01 | .03 | -.00 | .42 | .19 | .35 |  |  |
| Com. | -.10 | .00 | -.02 | -.05 | -.06 | -.03 | .42 | .20 | .38 | .50 |  |

## Results for Research Question #1

### Frequency of the aspects of work with data. Of the 236 instructional episodes used in the analysis, 170 (72%) were coded as involving one or more of the five aspects of work with data. As presented in Table 6, the five aspects of work with data occurred regularly. Making observations was found to be the least frequent of the five aspects, occurring in 24% of instructional episodes. Data modeling was the next most frequent aspect, occurring in 29% of the episodes, followed by asking questions (38%), generating data (43%), and communicating findings (again 43%).

As suggested by the proportions reported in Table 5, the different aspects of work with data often co-occurred within a single instructional episode. On average, there were 1.86 (*SD* = 1.61) aspects of work with data present during each instructional episode. This indicates that, on average, youth were engaged in around two of aspects of the work with data during each instructional episode. There was a considerable amount of variation in the extent to which these types of work with data were supported in each program.

Table 5. Proportion of signals for which each of the aspects of work with data was present

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

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

Taking the information criteria, likelihood ratio tests, and concerns of interpretability and parsimony into consideration when reviewing the models that converged, either a model one type, six profile solution or a model one type, seven profile solution was found to be most reasonable. The results from analyses using *both* sets of profiles were found to be comparable and so the six profile solution was chosen on the basis of parsimony and its greater interpretability.

The result of this model selection process was the estimation of *six distinct profiles* identified from the data, as presented in Figures 2 and 3. Figure 2 shows the profiles with variables that were centered to have a *mean* of 0 and a *standard deviation* of 1. Thus, the *y*-axis for this plot is labeled “Z-score”). Figure 3 shows the profiles with the raw data (not transformed). Thus, the *y*-axis for this plot is labeled “Value.” This solution represents the profiles of engagement identified to answer this research question and for use in subsequent analyses. The two plots are presented because they provide a different view into the composition of the profiles.

Figure 2. The six profiles of engagement (with variable values standardized)



Figure 3. The six profiles of engagement (with raw variable values)

The six profiles are characterized by both varying levels on both the indicators of engagement (cognitive, behavioral, and affective) and perceptions of challenge and competence. The results for research questions 3 and 4 use this solution and the six profiles in subsequent analyses. A MANOVA was carried out to determine whether the values of variables differ across the profiles, with multiple ANOVAs used to determine which variables (and for which profiles) there were differences. The MANOVA was statistically significant (*Pillai-Bartlett* = 0.633, *p* < .001). The *F*-tests associated with each ANOVA were also statistically significant. Descriptions of each the profiles taking account of their size (in terms of the number of responses for which the profile was most likely), their variable values, and what the profiles suggest about youth engagement are presented in Table 6.

Table 6. Descriptions of the six profiles

|  |  |  |
| --- | --- | --- |
| Profile | Percentage of All Responses | Description |
| Universally Low | 22.55 | Low levels of working hard, learning something new, and enjoying the activity, and perceptions challenge and competence. |
| Only Behaviorally Engaged | 12.51 | Moderate levels of enjoyment, low levels of hard work, and moderate levels of learning something new, challenge, and competence. |
| Only Affectively Engaged | 11.66 | Moderate levels of enjoyment, low levels of hard work, and moderate levels of learning something new, challenge, and competence. |
| All Moderate | 21.57 | This profile was characterized by moderate levels of the three indicators of working hard, learning something new, enjoying the activity, challenge, and competence. |
| Engaged and Competent But Not Challenged | 15.21 | This profile was characterized by high levels of working hard, learning something new, enjoying the activity, and competence, but low levels of challenge. |
| Full | 16.50 | This profile was characterized by high levels of working hard, learning something new, enjoying the activity, challenge, and competence. |

For all six profiles, the *ICC*s represent the variability (the proportion of variance explained) associated with each of the levels for each profile. These models show how much variability in the profiles was systematic at these different levels and was potentially attributable to youth, instructional episode, and program. The systematic variability at the youth level, for example, could be .10 for the *Full* profile and .025 for the *Universally Low* profile. At the program level, the *ICC*s were found to be small, with values ranging from 0.00 to 0.023, suggesting that little variability can be explained by the program. For the instructional episode level, the *ICC*s were also small, ranging from 0.004 to 0.01. Finally, at the youth level, the *ICC*s were larger: they ranged from .093 to .432. These *ICCs* show that there was substantial variability in the profiles present at the youth level, with less variability was explained by either the program youth were in or the nature of the particular instructional episode present when youth were signaled. These results set the stage for those for the next two research questions, on the relations between the aspects of work with data (for research question #3) and the youth characteristics (for research question #4) and the profiles of engagement.

## Results for Research Questions #3 and #4: Relations of aspects of work with data and youth characteristics and the profiles of engagement

In Table 7, each column represents the output from one of the six different models. As an example, the first column reports the coefficients for the associations between the predictor variables and the *Only behavioral* profile. Because the outcome was in the form of a probability (ranging from 0.00 to 1.00), it can be interpreted as the change in the probability of a response being associated with each profile. Note that the *p*-values were calculated using the most conservative and recommended by recent research Kenward-Rogers approximation (Halekoh & Hojsgaard, 2014).

Table 7. Findings for relations between the aspects of work with data and youth characteristics and the profiles of engagement.

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

*Note.* + p < .10; p < .05

The only engagement profile that was significantly associated with any aspects of work with data was the Full profile (see the column with the column name Full for these results). When program activities involved modeling data, youth were around 3% more likely to be fully engaged ( = 0.034 (0.017), *p* = .020; partial = .002). In other words, when program activities included modeling data, youth were more likely to report working harder, learning more, enjoying themselves more, and feeling more competent and challenged.

Youth were also more likely to be in the Full engagement profile when program activities included generating data ( = 0.027 (0.015), *p* = .033; partial = .002). These particular program activities increased the probability of full engagement by around 3%. To sum up these two findings, modeling data and generating data were associated with a (very) positive form of engagement, that exhibited by the Full profile. However, the effect sizes indicate quite small effects in substantive terms. Note that interactions between the individual aspects of work with data and youth characteristics were also specified. However, none of these interactions were found to be statistically significant.

Associations between youth characteristics and the six profiles are reported in the top half of Table 7. Youth who enter the program with higher levels of interest (in STEM) were more likely to report being in the engaged and competent but not challenged profile ( = 0.039, *p* = .009; partial = .001). In other words, youth who were more interested at the outset of the program report working harder, learning more, enjoying themselves more, and feeling more competent when they were involved in program activities, though they also report lower levels of challenge. For this effect, 17.879% would be needed to invalidate the inference, suggesting a moderately robust effect.

In terms of youths’ pre-program interest, these analyses show that youth who enter the program with higher levels of interest (in STEM) were more likely to report being in the *Engaged and competent but not challenged* profile ( = 0.039, *p* = .009; *partial*  = .001). For each one-unit increase in pre-program interest in STEM, youth were around 4% more likely to report this profile. In other words, youth who were more interested at the outset of the program report working harder, learning more, enjoying themselves more, and feeling more competent when they were involved in a program’s activities, though they also report lower levels of challenge. For this effect, 17.879% would be needed to invalidate the inference, a slightly larger value for the follow-up sensitivity analysis than those found for the (statistically significant) relations involving the aspects of work with data, suggesting a moderately robust effect.

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

# Discussion

Each of the disciplines that contribute to STEM learning - science, technology and computer science, engineering, and mathematics - involve work with data. In this study, engagement was used as a way to understand the experience of youth working with data during summer STEM programs. In particular, five aspects of work with data did occur regularly in the programs.

We identified six profiles of engagement using LPA. These profiles represented different configurations of how youth were working hard, learning, enjoying themselves, and feeling challenged and competent at the time they were signaled as part of the ESM approach. Relations of the five aspects of work with data and youth characteristics (pre-program interest in STEM and youths’ gender and status in terms of being a member of under-represented groups in STEM) were, overall, not strongly related with the profiles of engagement. However, some key findings were identified. Generating and modeling data were both related to the most potentially beneficial profile (full engagement), one characterized by high levels of all five of the engagement variables.

This study suggests that work with data and contemporary engagement theory as interpreted in this study can serve as a frame to understand what youth do in summer STEM programs. These findings also show the value of an innovative method, ESM, and an analytic approach designed to identify engagement holistically, LPA, that together to provide some access to youths’ experience in-the-moment of the activities they were involved in during the program. Data, and how youth and students in K-12 settings can themselves work with data, is an important, yet perhaps under-emphasized part of STEM learning. In the remainder of this section, we discuss key findings with respect to a) work with data, b) youths’ engagement, and c) what relates to youths’ engagement. Also, some limitations and recommendations for future research as well as implications for practice are identified and described.

## Key findings related to work with data in summer STEM programs

Results showed that work with data was common in the summer STEM programs. There was variability in *which* aspects of work with data was present: Making observations, in some form, occurred during 24% of the program’s time, for example, while generating data and communicating findings both occurred more frequently, during 43% of the instructional episodes. These findings, broadly, suggest that work with data occurred enough that we might expect to see differences in youths’ engagement. They align with what may be expected given past research: Such programs are designed to engage youth in the practices, including and as we argued earlier *especially* those relating to work with data, of STEM domains (Dabney et al., 2012; Elam et al., 2012). Even still, these are the first results of this kind (in terms of the proportion of the time spent in the programs). Using video-recording data and a sampling strategy that can provide insight into the amount of overall time spent was an important component of achieving these findings. While there are no other results of this particular kind, a related, an area of related work concerns other studies that have used the PQA measure.

## Key findings related to engagement

Six profiles of engagement were found using a rigorous model selection approach. In terms of comparing the make-up of the specific profiles to other, past research, little work has examined profiles of engagement. Schmidt et al. (2018) did examine profiles of engagement, which were constructed from indicators cognitive, behavioral, and affective engagement (but not perceptions of challenge and competence, as in this study). Schmidt et al. (2018) found six profiles, some of which partially overlap with those found in the present study. In particular, on the basis of the items shared between the studies, a *Universally low*, *All moderate*, and *Full* profile were found in both studies. However, as these profiles are characterized by the (uniform) level across all of the variables, this is only limited evidence for the presence of these profiles in the larger population of youth engaged in science and STEM-related learning activities. The number of profiles found is broadly similar to that found in past researcg: Schmidt et al. (2018) found six profiles of engagement.

The six profiles lend insight into how youth engage during summer STEM programs. In particular, both the *Only behavioral*, *Only affective*, and *Engaged and competent but not challenged* profiles were found in the present study, but not in Schmidt et al.’s (2018) study. Youth were highly engaged (as may be anticipated given the goals and design of such programs), but perceive a misalignment between their (high) competence and how (not very) challenged they were. According to past theory (e.g., Csikszentmihalyi, 1997) and some research (e.g., Shernoff et al., 2016), such a profile would be unexpected, as high levels of engagement are expected to be associated with high levels of *both* challenge and competence. In this study, a profile characterized by high competence but (very) low challenge was associated with very high engagement. This profile, *Engaged and competent but not challenged*, then, seems to suggest a type of engagement that may be unique and common to summer STEM programs. Perhaps such a profile may be expected given the lower stakes (compared to formal educational settings) of summer STEM programs (and other informal learning environments) and the degree of competence that youth–many of whom have chosen to attend the particular program (Beymer et al., 2018)–perceive during them.

In addition to suggesting a profile of engagement that is distinct to summer STEM program, this profile and the other two not found in past research have some implications for youth activity leaders. In particular, they suggest that lower challenge may *not*, as would be anticipated given theory and past research (i.e., Csikszentmihalyi, 1990; Shernoff et al., 2016), be associated with lower engagement. This may suggest that activities that are not challenging but have other possible benefits to youth (i.e., benefits from activities designed to support youths’ social skills), can be integrated into programs, along with other, more challenging activities that are also engaging.

## Key findings related to work with data and youth characteristics and their relations to engagement

Why might these relations be so minimal? First, and foremost, the little variability at the instructional episode level was noteworthy because it means that few relations between variables at the instructional episode were expected. In particular, there were small ICCs at the instructional episode level for all six profiles. This suggests that there was very little systematic variability at the particular level that a variable for work with data was at. Additionally, the ICC values found in this study were smaller than those found in the one other past study that employed the same analytic approach (Strati et al., 2017). The relative absence of variability at the instructional episode level may be due to the summer STEM setting: Perhaps youth are less likely to engage differently from instructional episode to instructional episode (compared to in K-12 educational settings) because there is less variability in what took place across the episodes or because youth perceive there to be lower stakes for the programs’ activities and therefore do not perceive the changes in the instructional episode as a salient factor in terms of their engagement. This consideration is described in greater detail in the limitations section.

Even so, there were *some* noteworthy findings that could be anticipated on the basis of the importance of the two aspects of work with data that were found to relate positively to youths’ engagement. In particular, both generating and modeling data were found to be positively (and statistically significantly) related to the *Full* profile, suggesting that when youth were involved in these practices, then they were more likely to be highly engaged. This suggests that when youth were involved in these aspects of work with data, they were more likely to report high levels of cognitive, behavioral, and affective engagement, and high perceptions of competence and challenge. Generating and modeling data may have such relations because they were particularly important aspects of work with data. As Lehrer and Schauble (2006) explain, *inscriptions serve commitments*: Choosing to record an observation or an idea as data involves the process of identifying something that is worth recording and then recording the parts that are of interest. Thus, generating data may be fully engaging to youth because it is, generally, demanding and important with respect to work with data. Modeling, too, is an important practice. It has been described as *the* central scientific and engineering practice (Lehrer & Schauble, 2015; Weisberg, 2012), and its relations with full engagement provides some actionable evidence for its importance in the context of summer STEM programs. Modeling may be especially engaging to youth because such work positions learners as the creators of new information, in addition to using models created by others to learn about authoritative sources of information. This is one of the affordances of modeling in teaching and learning contexts (Berland et al., 2016; Schwarz et al., 2009). Moreover, when learners create new knowledge through activities such as modeling, they can begin to shape the process of constructing new knowledge in a domain, a challenge in science education contexts (Stroupe, 2014) and likely in other STEM content areas, we well.

These findings suggest that work with data may not be more engaging *per se*. Instead, it may be the way that youth engage in them that matters, in alignment with past research (Berland et al., 2017). While the findings for this question were somewhat minimal, there are key findings from both the important relationships that were found to be statistically significant (between generating data and data modeling and *Full* engagement) and from those that were not. Other samples, other enactments of work with data, and, possibly, other analytic approaches can build on this work to further substantiate what is known about how work with data engages youth and other learners.

There were not many relations in terms of youths’ gender, URM status, or pre-program interest, which was surprising because there *was* substantial variability in the profiles of engagement at the youth level. This was also surprising as past theory and research have suggested that learners’ gender, URM status, and individual or pre-program interest can predict engagement (Bystydzienski, Eisenhart, & Bruning, 2015; Hidi & Renninger, 2006; Shernoff & Schmidt, 2008). There was one relation that was noteworthy: youth with higher pre-program interest were found to be more likely to be *Engaged and competent but not challenged*. This suggests that youth with a higher interest in STEM were inclined to be highly engaged and good at what they were doing, but were not challenged by the activities they experience. This finding is in line with past research suggesting a relationship (direct or as a moderator) between youth characteristics (including interest) and their engagement (Shernoff et al., 2003; Shernoff et al., 2016; Strati et al., 2017). More specifically, this finding suggests that for youth who were particularly interested (and those who choose to attend) summer STEM programs, what they were involved in may not challenge them very highly. This finding has implications for past research that shows youth who choose to attend summer STEM programs were more engaged (but that does not speak to their degree of challenge; Beymer, Rosenberg, Schmidt, & Naftzger, 2018).

## Limitations to the present study and recommendations for research

One limitation concerns the programs: The programs included in this study were not designed especially to support youth in work with data. Instead, the programs were designed around best practices for summer STEM programs to support youth to engage in a wide variety of STEM-related practices–and in other activities, such as those intended to build a sense of camaraderie among the youth in the programs. In this study, aspects of work with data were identified and were found to be common, but some of the heterogeneity in the nature of working with data may be due to this reason: Planning and instruction for the programs did not aim to foster rich work with data any more than the other activities (STEM and otherwise) that made up their programming.

In addition to the varied ways in which youth worked with data, some of the relations of the variables for the five aspects of work with data to youths’ engagement may be due to the ways that the variables for work with data indicated, in fact, many different ways of working with data, some ambitious, others more innocuous. These two types of working with data were considered the same in the variables used to predict youths’ engagement. Future research can aim to understand youths’ engagement in outside-of-school data science programs and K-12 units, for example, that are focused more on work with data to understand better how work with data engages youth. Nevertheless, this study does provide insight into how work with data took place during *model* (i.e., designed around best practices for such programs) summer STEM programs and how such work relates to youths’ engagement.

Finally, there were some general measurement-related limitations. Work with data can be difficult to measure because, as the qualitative analysis revealed, there were a variety of ways in which youth can be involved in work with data. McNeill and Berland (2017) describe a similar type of disagreement across science education settings: While a limitation, the coding frame did represent agreement across a range of studies across STEM contexts for the aspects of work with data. In terms of the alignment of the measure with the conceptual framework for work with data, the dimensions of the STEM-PQA measure aligned closely with the aspects of work with data. However, there were some divergences that may have had an impact upon some of the findings. For example, for the interpreting and communicating findings code, the STEM-PQA codes for *Analyze* (“Staff support youth in analyzing data to draw conclusions”) and *Use symbols or models* (“Staff support youth in conveying STEM concepts through symbols, models, or other nonverbal language”) were used. In the case of the latter STEM-PQA code, conveying STEM concepts through symbols, models, or other nonverbal language could have reflected instructional episodes in which youth used, for example, mathematical equations or formulas, but did not do so as part of modeling data of a phenomena in the world: They could have simply been using an equation outside of the context of any particular phenomena. Future research may consider the usefulness of coding for this aspect of work with data (and this aspect of science curricular standards in particular; see NGSS Lead States, 2013).

## Implications for Practice

A few implications for practice can be drawn from this study, though these are somewhat restricted given the minimal findings. First, *generating data* and *modeling data*, in particular, may be beneficial in terms of engaging youth. Youth activity leaders (in summer STEM and other STEM enrichment contexts) and teachers (in *formal* learning environments) can best include the beneficial practices of generating and modeling data not in isolation, but rather through involving youth and learners in complete cycles of an investigation. This aligns with both foundational and contemporary research on work with data in education (Berland et al., 2018; McNeill & Berland, 2017; Hancock et al., 1992; Lee & Wilkerson, 2018).

Another implication concerns how work with data was enacted. As found in this study, work with data (and even specific aspects of work with data, such as asking questions) does not involve activities that are enacted in a universal way. An instructor instead of youth interpreting and communicating findings, for example, or learners asking general, conceptual questions about work with data, as another, are different from youth working to interpret findings and figuring out how to ask a question that can be answered with data, respectively. This heterogeneity suggests to those involved in planning and enacting engaging activities that involve data to consider *who* works with data carefully, *how* they do so, and *how much time and sustained focus* is required for such activities to be carried out. This implication aligns with recent curricular reform efforts, some of which suggest that involving work in STEM-related practices is most effective when it involves learner-driven (but instructor-supported) iterative processes of identifying a question or problem, marshaling sources of data that can be used to figure out what is happening, and developing model-based explanations that are shared with the learning community (National Governors Association, 2013; National Research Council, 2012; NGSS Lead States, 2013). While just two implications, youth activity leaders and teachers and those designing data-rich activities and evaluating the impacts of instruction based on such activities can use the findings from this study as a starting point to consider how engaging in work with data may also prepare learners to think of, understand, and take action based on data in education and in other areas of their lives.

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1. These signals were at the same time for all of the youth within their program, but at different times between programs and between days within programs (with the constraint that no two signals could occur less than ten minutes apart). [↑](#footnote-ref-1)
2. See Supplementary Material B for the alignment between the STEM-PQA and the aspects of work with data. [↑](#footnote-ref-2)
3. This measure was constructed by taking the maximum value for the scales for the different content areas (science, mathematics, and engineering), so that the value for a youth whose response for the science scale was 2.5 and for the mathematics scale was 2.75 would be 2.75. See Beymer, Rosenberg, and Schmidt (2018) for more details on this (use of the maximum value) measurement approach. [↑](#footnote-ref-3)
4. Youth and the instructional episode can be considered to be crossed with both nested within the program. [↑](#footnote-ref-4)